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USE OF COMPUTER SIMULATION MODELING TO ASSESS UTILITIES OF PERSONNEL CLASSIFICATION DECISIONS

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CONTENTS

TABLES

FIGURES

PREFACE

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USE OF COMPUTER SIMULATION MODELING TO ASSESS UTILITIES OF PERSONNEL CLASSIFICATION DECISIONS

SUMMARY

Limitations to traditional approaches for assessing utilities of human resource interventions (e.g., selection procedures) are noted and computer simulation modeling (CSM) is described as a more general and flexible alternative. To establish the fidelity of CSM as an alternative to analytic utility models, results presented previously on a Time to Proficiency (TTP) model were replicated using CSM in Study I. In Study II, a CSM of an interdependent four-job system was developed in order to evaluate tradeoffs in job outcomes associated with alternative personnel classification policies. Results supported the ideas that (a) human resource interventions (e.g., implementaiton of a selection system) in one job cannot be viewed in isolation independently of their effects on other, interdependent jobs, and (b) system-wide, rather than individual job payoffs, represent more appropriate optimization criteria for interdependent multiple-job systems.

I. INTRODUCTION

Background

Like the private sector, the U.S. Air Force (USAF) has an interest in assessing the payoffs, or utilities, of its human resource management (HRM) activities (Matthews, 1987; Matthews & Looper, 1990). Questions regarding program utility involve more than determining the effectiveness of HRM programs in bringing about desired results (Boudreau, 1991; Goldstein, 1980; Schmitt & Robertson, 1990); they concern assessments of overall HRM program contributions to organizational criteria (e.g., dollar volume sales, profit, readiness) relative to program costs. Numerous approaches to assessing the utility of HRM programs have been proposed, including (a) expectancy charts (Cascio, 1982), (b) utility analysis (Raju, Burke, & Normand, 1990; Schmidt, Hunter, McKenzie, & Muldrow, 1979; Schmidt, Hunter, Outerbridge, & Trattner, 1986) (c) break-even analysis (Cascio, 1982), (d) analyses based on firm-specific human capital theory (Joll, McKenna, McNabb, & Shorey, 1983; Steffy & Maurer, 1986), (e) human resource accounting (Flamholtz, 1985), and (f) analyses of cost/performance tradeoffs (Armor, Fernandez, Bers, & Schwarzbach, 1982).

The most thoroughly developed models for assessing the organizational value of HRM programs are based on utility analysis (Boudreau, 1991; Raju et al., 1990; Steffy & Maurer, 1986; Vance & Colella, 1990). Developments in utility analysis can be traced back over 70 years (Hull, 1928; Kelley, 1923), but Schmidt and Hunter (1977) and Schmidt et al., (1979) are usually credited with initiating the more contemporary work on utility analysis. More recent literature has presented a number of extensions and embellishments to Schmidt and Hunter's basic utility models (e.g., Becker & Hueslid, 1992; Bobko, Karren, & Kerkar, 1987; Boudreau, 1983a, 1983b, 1991; Boudreau & Berger, 1985; Boudreau & Rynes, 1985; Burke & Doran, 1989; Burke & Frederick, 1986; Cascio & Morris, 1990; Cascio & Ramos, 1986; Cascio & Silbey, 1979; Cronshaw & Alexander, 1985, 1991; Eaton, Wing, & Mitchell, 1985; Florin-Thuma & Boudreau, 1987; Greer & Cascio, 1987; Hunter & Hunter, 1984; Hunter, Schmidt, & Coggin, 1988; Judiesch, Schmidt, & Mount, 1992; Landy, Farr, & Jacobs,

1982; Mathieu & Leonard, 1987; Orr, Sackett, & Mercer, 1989; Raju et al., 1990; Raju, Burke, Normand, & Langlois, 1991; Reilly & Smither, 1985; Schmidt & Hunter, 1983; Schmidt, Law, Hunter, Rothstein, Pearlman, & McDaniel, 1993; Weekley, Frank, O'Connor, & Peters, 1985). However, most of these are based on Brogden's (1949) and Cronbach and Gleser's (1965) early developments, or what we will refer to as a traditional analytic approach to utility analysis.

Traditional Algebraic Approaches to Utility Analysis

Traditional approaches to the assessment of HRM program utility are based on the Brogden-Cronbach-Gleser (BCG) model for assessing test utility in financial terms. Most of these approaches can be expressed as some variant or extension of the following equation (Schmidt et al., 1979):

$$\Delta U = (T)(N_s)(SD_y)(r_{xy})(Z_x) - (C_a)(N_a), \qquad (1)$$

where (in the case of evaluating the utility of a selection program) ΔU is the total dollar value utility resulting from use of the selection system (e.g., test), T is the time period duration of the selection program (e.g., number of years), N_s is the number of selectees (the number of "treated" individuals), SD_y is the standard deviation of performance in the unselected population in dollars, r_{xy} is the validity of the test, Z_x is the average standardized test score in the group of selectees, C_a is the per-applicant cost of testing, and N_a is the number of applicants. Published applications of algebraic utility models such as in Equation 1 now exist in several areas of research (see Boudreau, 1991).

Despite the widespread acceptance of traditional utility models and their more recent embellishments, there are several limitations to them, both generally, and with respect to assessing HRM program value in the military (e.g., Matthews, 1987; Vance & Colella, 1990).

First, traditional utility models are based on the general linear model and, consequently, require assumptions of (a) normally distributed predictor and criterion scores, and (b) linearity and additivity in equations (Johnston, 1984). However, predictor score distributions may often be markedly nonnormal (Micceri, 1989). This may occur, for example, when selection is from (a) a group of self-selected, highly recruited applicants (Murphy, 1986), or (b) an internal, preselected group, such as is the case for training or promotion decisions. Criterion scores can also be nonnormal and would be expected to more nonnormal (i.e., negatively skewed and leptokurtic) to the extent that effective HRM programs (e.g., selection, placement, and training systems) are in use. The linearity assumption should also be questioned given evidence of (a) changing test validities over time (Deadrick & Madigan, 1990; Henry & Hulin, 1987, 1989; Hulin, Henry, & Noon, 1990; Murphy, 1989), (b) situational constraints that place ceilings on productivity (Eulberg, O'Connor, Peters, & Watson, 1984; O'Connor, Eulberg, Peters, & Watson, 1984; Peters & O'Connor, 1980; Steel & Mento, 1989), and (c) actual nonlinearities and discontinuities in HRM practice (e.g., promotability is not a constant, linear, function of tenure, but rather is only assessed at discrete career points).

Second, traditional utility models are also analytic in that they use algebraic expressions to solve for estimates of HRM program utility. One consequence of adopting an analytic approach has been the derivation of extremely complex algebraic expressions (e.g., Boudreau, 1983b, 1991; Boudreau & Berger, 1985; Steffy & Maurer, 1986). As a result, nearly all applications of utility analysis have been

limited to simple single-predictor- single-criterion relationships for one job at a time (Lance, 1987). This narrow focus is unrealistic because (a) several factors (e.g., ability, experience) are likely to impact performance simultaneously, (b) multiple, interrelated, productivity-enhancing HRM programs may be in effect simultaneously, (c) "selection" decisions may actually be classification decisions in which candidates are simultaneously considered for multiple position openings, and (d) there may be lateral movement across jobs after organizational entry (Blumberg, 1980; Downs, 1985; Skinner, 1983).

A third limitation to traditional analytic approaches to utility analysis is their focus on static or stationary processes. The static nature of many utility models may not be realistic in operational settings. For example, one implicit assumption relating to Equation 1 is that utilities are constant for multiple cohorts (e.g. Z_x is constant across cohorts). This assumption may be unreasonable given the changing demographic characteristics of the U. S. workforce. Also, performance is implicitly assumed to be constant across experience levels (i.e., $(SD_y)(r_{xy})(Z_x)$ is multiplied by the constant T, or average tenure). Counter to this assumption, Alley and Teachout (1992), Lance, Hedge, and Alley (1989), McDaniel, Schmidt, and Hunter (1988), and Schmidt, Hunter, Outerbridge, and Goff (1988) have shown that increased experience leads to increased performance; that is, that performance varies predictably over time. Test validity also is assumed to be constant across employee tenure (i.e., r_{xy} is constant across T time periods). Contrary to this assumption, Henry and Hulin (1987), among others, have shown that validities decline over employee tenure, and Lance et al. (1989) have shown that, relative to contributions from increased experience, aptitude contributions to performance diminish over time.

A final limitation of traditional utility models that is particularly relevant to the military is that their algebraic complexity has prohibited the development of appropriate models for classification decisions. As mentioned above, this limitation should be of particular concern to the military since one of the primary ways in which the military can achieve a more efficient use of available manpower is by better matching enlistee characteristics with those needed in job position openings.

Time-to-Proficiency Model

Carpenter, Monaco, O'Mara, and Teachout (1989) dealt with some of the limitations to traditional approaches to utility analysis in the military in their Time to Proficiency (TTP) model. This model defines performance in terms of productive capacity, or individual proficiency (performance time, or relatedly, the number of work units completed per unit time) relative to a standard of maximum possible proficiency, and in relation to costs incurred to procure productivity. The TTP model consists of three algebraic submodels of changes over the first term of enlistment, in (a) individual productive capacity, (b) manpower, through attrition, and (c) costs to procure productivity. The productive capacity component models changes in individual productive capacity over the first term of enlistment as a function of aptitude and accrued experience. The cost component tracks and cumulates training and salary costs for airmen retained over the first term. The attrition component models the probability, conditional on individual aptitude, of an individual remaining in service after a given number of months. An integration of these three submodels allows assessments of (a) total (organizational) productive capacity realized as a function of retained incumbent experience and aptitude level, (b) realized productive capacity relative to costs incurred for different aptitude groups,

(c) experience/aptitude tradeoffs for a given level of productive capacity, and (d) optimal aptitude cut scores given costs per productive unit, time to achieve proficiency, and contribution of aptitude to productive capacity.

Carpenter et al. (1989) demonstrated the success of the TTP model in linking aptitude scores, job proficiency measures, and supervisor estimates of productive capacity to estimates of costs per productive unit in one Air Force Specialty (AFS), (Avionics Communications Specialist - AFS 328x0). They recommended that results be extended to additional specialties considered independently and, eventually, simultaneously in a multiple-job system. The work reported here, in part, addressed these recommendations using computer simulation modeling.

A Computer Simulation Modeling Approach to Utility Analysis

Analytic approaches to utility analysis use mathematical relationships to obtain exact solutions to questions of interest (e.g., dollar-value utility of using Test X for T years). Simulation models, on the other hand, seek numeric estimates of system characteristics. Simulation models may be static (e.g., Monte Carlo simulations) or dynamic (modeling characteristics of a system that evolves over time) and deterministic or stochastic, depending upon whether models contain ramdom error components (Law & Kelton, 1982). Computer simulation modeling (CSM) has been used widely in management areas such as production, finance, and marketing (Ledvinka & Ladd, 1987), but rarely has been used to study problems in HRM (however, see Kroeck, Barrett, & Alexander, 1983; Ledvinka, Markos, & Ladd, 1982).

Ledvinka and Ladd (1987) argued that CSM is a viable alternative approach to assessing HRM program utility, and that CSM is not subject to many of the limitations to conventional, analytic utility models. For example, nonnormal predictor distributions are easily modeled by defining hypothetical test score distributions that are representative of applicants' actual scores, and sampling randomly from the distribution in repeated simulations. CSM can also represent nonstationary processes by allowing certain system variables to vary endogenously as functions of other system variables. Simulated outcomes (e.g., individual productive capacity, unit effectiveness) may be defined in terms of any metric, including dollar-value-payoff, or costs to attain a given level of performance. Also, nonlinearities and discontinuities in relationships among variables can be modeled by simulating the occurrence of events only at (perhaps irregular) predetermined intervals. Perhaps most importantly, CSM affords the possibility of estimating utilities simultaneously for multiple, and interrelated (a) criterion variables, (b) productivity-enhancing HRM interventions, and (c) job classes (i.e., classification decisions), in dynamic job systems (Ledvinka & Ladd, 1987). The algebraic complexity of traditional utility models has been one of the major stumbling blocks to extending traditional utility analysis to these problems.

Summary and R&D Purpose

The preceding discussion highlights some of the limitations to current analytical approaches to utility analysis, most of which are based on the BCG model. Computer simulation modeling is viewed as a viable alternative to traditional analytical approaches (a) in order to extend utility analysis beyond

restrictive statistical assumptions of traditional utility models, (b) because it is more easily adaptable to particular characteristics of the military context (e.g., payoffs are not limited to dollar payoff metrics), and (c) because it provides a tractable means for the assessing payoffs of alternative personnel classification strategies. Thus, the purposes of the work reported here were to (a) demonstrate computer simulation modeling (CSM) alternative approach to utility analysis, (b) replicate Carpenter et al.'s (1989) TTP results using CSM to establish the fidelity of the computer simulation approach adopted here, and (c) develop and evaluate prototype CSM procedures for assessing the overall utility of personnel classification decisions.

General Programming Requirements

All of the simulations reported here were conducted using a general management planning simulation model (MPlanSim) described by Ladd and Kudisch (1994). MPlanSim has been developed exclusively for the Apple MacIntosh environment. General programming requirements of MPlanSim are specifications of:

(a) state variables, for example, applicant pools, job categories (e.g., specialty assignment, training status), and termination categories (e.g., dismissal, non-reelistment, retirement);

(b) individual-level attributes (variables) representing characteristics of simulated entities (e.g., individuals) within the system states, for example, aptitude, experience, job performance, and tenure. MPlanSim also provides for the specification of state-level (e.g., job-level) as well as simulation-wide (global) variables;

(c) rules governing entities' movement across system states, for example, (i) classification of enlistees into jobs based on analysis of the fit between enlistees' characteristics and those required for effective job performance, (ii) graduation from training based on elapsed time and achievement of minimum end-of-course grades, or (iii) promotion based on a combination of tenure and performance requirements;

(d) processes by which entities are "moved" across system states, for example, conditional or unconditional Markov (push) or renewal (pull) processes;

(e) methods for computing new variables or new values for existing variables, for example, computing productive capacity as a function of aptitude and experience, updating productive capacity as a function of accrued experience, or summing training and salary costs incurred for performance;

(f) means for relating individual- and state-level variables to assessment of overall system utility.

MPlanSim maintains a detailed record of system information throughout the duration of the simulation and allows calculation of summary statistics upon completion of the simulation (e.g., number of individuals retained in Job X after T months, total costs incurred over T months, total system utility after T months).

II. STUDY I: REPLICATION OF THE TTP MODEL

The purpose of Study I was to replicate the algebraic results obtained by Carpenter et al. (1989) on the TTP model using CSM to establish the fidelity of CSM for assessing utility in a single-job system. In the following sections we (a) review the algebraic approach and results presented by Carpenter et al. (1989) for the three TTP model components (Attrition, Cost, and Productive Capacity models) as well as the Integrated Model which combines these three components, (b) document the translation of the TTP model into a comparable CSM using MPlanSim, and (c) validate CSM results by comparing them to those presented originally by Carpenter et al. (1989).

TTP Model

TTP Attrition Submodel. Carpenter et al. (1989) modeled attrition of first-term enlistees as the percentage of airmen remaining in the USAF after a given number of months conditional upon level of cognitive ability, under the rationale that different attrition rates are observed among groups of airmen differing in mean level of cognitive ability. Data were obtained from the Defense Manpower Data Center (DMDC) for the 1982 cohort group for all incumbents of Air Force Specialties (AFSs) whose AFS codes (AFSCs) began with "32" in order to track time of separation over the first 48 months. Time of separation was recorded separately for airmen grouped according to Electronics score deciles (i.e., airmen were grouped according to Electronics score percentile ranges 60-69, 70-79, 80-89, and 90-99). The following algebraic model was developed by Carpenter et al. (1989) to define the family of curves describing the probability of remaining in the USAF as a function of months of service and aptitude level (Electronics score):

$$pr(\underline{x},\underline{t}) = \underline{b}_0 + \underline{b}_1 \ln[(\underline{t} + s(\underline{x}))/(48 - \underline{t})] + \underline{b}_4\underline{x} \tag{2a}$$

where

$$s(\underline{x}) = \exp(\underline{b}_2 + \underline{b}_3\underline{x}) \tag{2b}$$

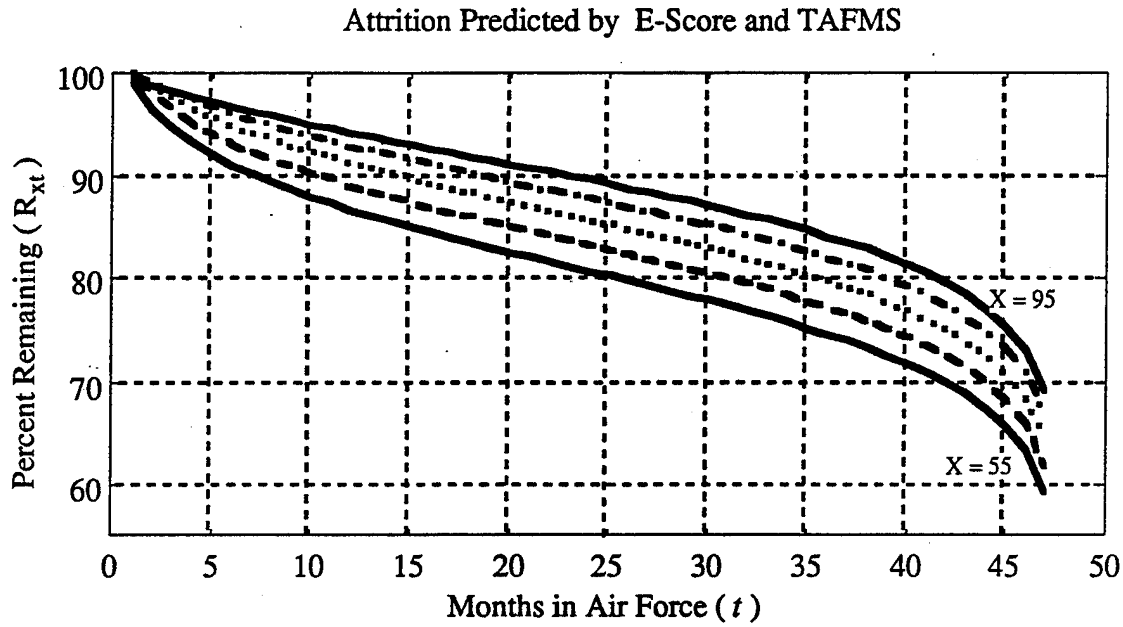
Here, $pr(\underline{x},\underline{t})$ represents the percentage of airmen with aptitude level of $\underline{x}$ remaining in the USAF after $\underline{t}$ months ($\underline{t} \leq 48$), $\underline{x}$ represents the Armed Services Vocational Aptitude Battery (ASVAB) Electronics composite percentile score, $\underline{t}$ refers to the number of months of service, and $\underline{b}_0$ through $\underline{b}_4$ represent parameters to be estimated. Application of nonlinear regression yielded the following parameter estimates:

$$pr(\underline{x},\underline{t}) = 66.0881 - 5.5569 \ln[(\underline{t} + s(\underline{x}))/(48 - \underline{t})] + .2679\underline{x}$$

where

$$s(\underline{x}) = \exp(.0654\underline{x} - 3.8500) \tag{3}$$

As Carpenter et al. (1989) indicated, this model fit observed attrition rates well, with $\underline{R}^2 = 0.9898$. A plot of this function (i.e., percentage of airmen remaining in the USAF after $\underline{t}$ months) for aptitude levels 55, 65, 75, 85, and 95 (i.e., the midpoints of the Electronics score deciles) is shown in Figure 1, which is a reproduction of Carpenter et al.'s (1989) Figure 12.



$$R_{xt} = 66.0881 + .2679x - 5.5569 \log \frac{t + sx}{48 - t}$$

X= ElectronicScore[55 65 75 85 95]

$sx = e^{0654x-3.85}$

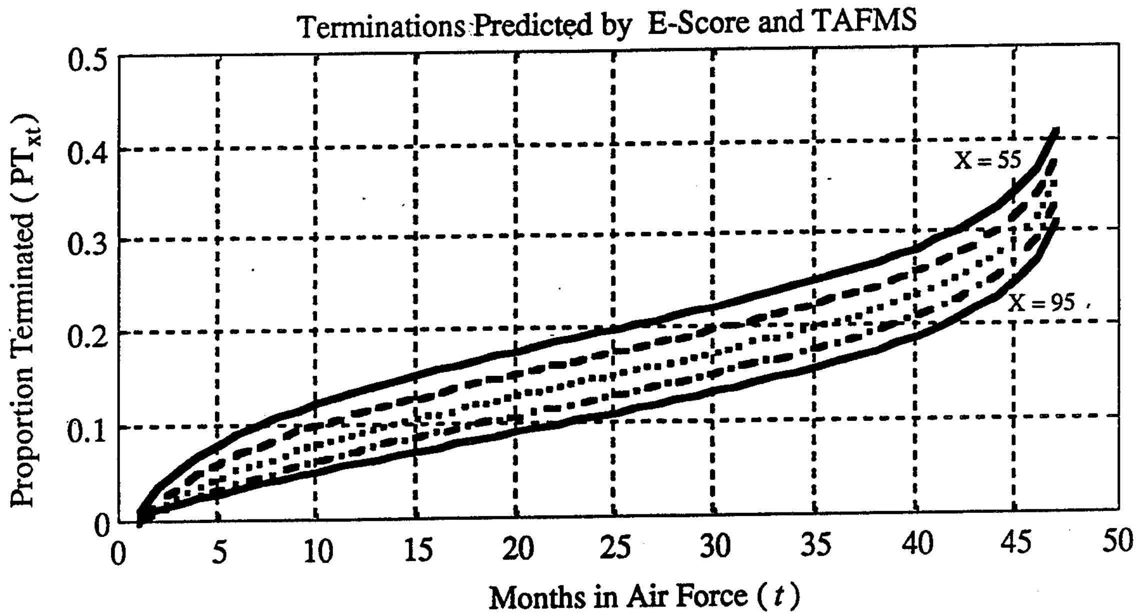
Figure 1: TTP Attrition Model

<u>CSM Attrition Submodel</u>. Several translations were necessary between the TTP and CSM Attrition submodels. First, the approach taken by Carpenter et al. (1989) was to model the <u>percentage of airmen remaining</u> after <u>t</u> months as a function of aptitude. On the other hand, since MPlanSim creates simulated individuals whose probability of termination is calculated repeatedly upon each iteration of the simulation, it was necessary to translate the TTP model into a model of discrete, individual-level termination probabilities associated with each simulated time period (i.e., month).

The first step was to convert Equation 3 (percent remaining) into a proportion (probability of remaining) by dividing by 100. Subtracting this from 1.00 yields the cumulative proportion of airmen <u>terminated</u> (rather than remaining) through month <u>t</u> and as a function of aptitude:

$$pt(\underline{x},\underline{t}) = 1 - pr(\underline{x},\underline{t})/100 \qquad (4a)$$

$$= .33912 + .055569 \ln[(\underline{t}+s(\underline{x}))/(48-\underline{t})] - .002679\underline{x} \qquad (4b)$$



$$PT_{xt} = 1 - \frac{R_{xt}}{100} = .33912 - .002679x + .055569 \log \frac{t+sx}{48-t}$$

$$R_{xt} = 66.0881 + .2679x - 5.5569 \log \frac{t+sx}{48-t}$$

X= ElectronicScore[55 65 75 85 95]

$$sx = e^{.0654x-3.85}$$

Figure 2: CSM Implementation of TTP Attrition Model

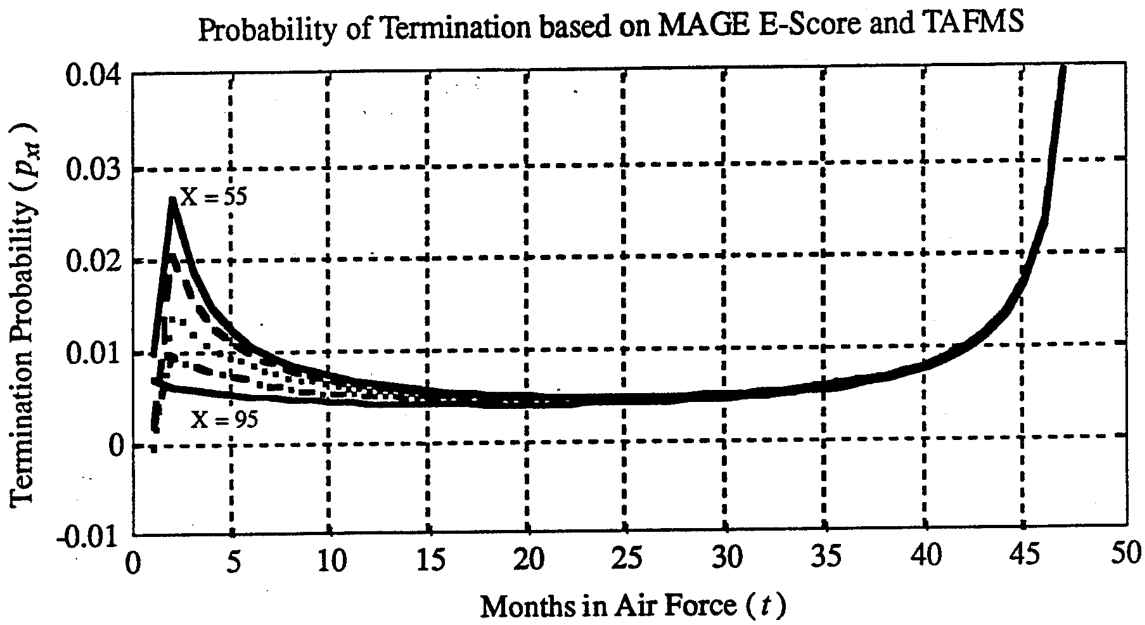
A plot of Equation 4, depicting the cumulative proportion of airmen terminated as a function of aptitude group is shown in Figure 2.

Second, since MPlanSim treats time as a discrete variable, is was necessary to transform Equation 4 describing the cumulative proportion of airmen terminated through month $\underline{t}$ into an expression which described the proportion of airmen terminated during any specific time period (i.e., month) of the simulation. This may be obtained from the difference equation:

$$pt_i(\underline{x},\underline{t}) = pt(\underline{x},\underline{t})_{t=i} - pt(\underline{x},\underline{t})_{t=i-1} \tag{5}$$

Substituting from Equation 4, this can be expressed as:

$$pt_i(\underline{x},\underline{t}) = -.055569\ln[(\underline{t}-1+s(\underline{x}))/(48-(\underline{t}-1))] + .055569\ln[(\underline{t}+s(\underline{x}))/(48-\underline{t})]. \tag{6}$$



$$p_x = -.055569\log\frac{sx+t-1}{49-t} + .055569\log\frac{sx+t}{48-t}$$

X= Electronics Score [55 65 75 85 95]

$$sx = e^{.0654x-3.85}$$

Figure 3: CSM Monthly Termination Probabilities

Thus $pt_i(\underline{x},\underline{t})$ represents the proportion of airmen of a given aptitude level terminated in month $\underline{t}$ as the difference between the cumulative proportion of airmen terminated up through the previous month and the cumulative proportion terminated up through the current month ($-.055569\ln[(\underline{t}-1+s(\underline{x}))/(49-\underline{t})] + 0.055569\ln[(\underline{t}+s(\underline{x}))/(49-\underline{t})]$). A plot of the monthly probability of termination as a function of tenure for the different aptitude deciles is shown in Figure 3.

The equivalence of Equations 4 and 6 can be demonstrated by comparing the values of Equation 4 <u>at</u> month 47 for different aptitude levels to a summation of values obtained from Equation 6 <u>across</u> the first 47 months (both Equation 4 and Equation 6 are undefined at month 48 since division by zero occurs, the net effect of which is to confine parameter values to the first term of enlistment). These results are shown in Table 1. Values in Table 1 are identical, confirming the mathematical equivalence of Equations 4 and 6.

The Attrition portion of the TTP model was implemented in MPlanSim as a conditional Markov process with termination probabilities determined from Equation 6 as a function of two variables: Tenure (months of service) and Electronics (ASVAB Electronics composite percentile score). Variables and termination probabilities were initialized prior to the first simulated time period (month) in the CSM as follows:

Tenure = 0, i.e., time period equals Month 0;

Electronics = Round(ASVAB(Uniform(0,1)), i.e., an Electronics score was assigned to each simulated individual by randomly selecting a real number from a uniform distribution bounded by 0 and 1.00 and rounding it to two digits to represent a percentile score;
s($\underline{x}$) = exp(0.0654*Electronics - 3.85), from Equation 3b, and;

QuitProb = pt($\underline{x}$,$\underline{t}$) = 0, indicating that the probability of termination is zero prior to commencing the simulation.

Table 1.

Cumulative Proportion Terminated Through Month 47 by Aptitude Level

	Aptitude Decile Median				
	55	65	75	85	95
Carpenter et al. (1989) Equation 4 - Value at Month 47	.41	.38	.36	.33	.31
Difference Model Equation 6 - Sum of Months 1 to 47	.41	.38	.36	.33	.31

Thus, prior to the first month of the simulation, each simulated individual was assigned an Electronics percentile score, had zero tenure, and had zero probability of termination. s($\underline{x}$) was initialized at this point at a value which would remain a constant throughout the simulation because it is strictly a function of Electronics score which, once determined, also remains constant. At the end of the first time period, (i.e., $\underline{t} > 1$), values on the following variables for the individuals remaining in the simulation were recalculated as:

Tenure = Tenure + 1, i.e., Tenure was incremented by 1 each month that simulated individuals remained in the simulation.

QuitProb = pt_i($\underline{x}$,$\underline{t}$) = -.055569ln[($\underline{t}$-1+s($\underline{x}$))/(49-$\underline{t}$)] + .055569ln[($\underline{t}$+s($\underline{x}$))/(48-$\underline{t}$)], from Equation 6.

Thus, Electronics and s($\underline{x}$) scores remained constant throughout the simulation, while scores on Tenure and QuitProb were recalculated for each time period. At the beginning of each new time

period (month), a proportion of individuals corresponding to the value of QuitProb was terminated, or exited from the simulation. Thus, QuitProb defined the Markov probability of termination conditional on Tenure and Electronics score.

TTP Cost Submodel. Carpenter et al. (1989) modeled costs to procure productivity as a function of initial recruiting costs and training costs incurred during the first 10 months, as well as salary costs with pay increases following an average promotion schedule. Carpenter et al. (1989) obtained data from Air Training Command Cost Factors (June, 1987) to estimate these costs. Resulting estimated costs across the first term of enlistment were shown in Carpenter et al.'s (1989) Figure 13 reproduced here as Figure 4.

CSM Cost Model. The TTP Cost submodel was implemented directly in the CSM as a conditional function of Tenure. As one option in the MPlanSim software, variables may be defined as conditional or unconditional functions of other variables by simply specifying the values assigned to certain variables as a function of other variables' values. Functions may take any form and thus need not be linear, continuous, or monotonic. In order to translate the TTP Cost model into the present CSM, a function ("A328Cost") was created in MPlanSim which specified costs as a function of Tenure as shown in Carpenter et al.'s (1989) Figure 13 (i.e., Cost = A328Cost(Tenure)). The function "A328Cost" is shown in Figure 5. This function defines costs incurred for each month of the first term of enlistment. The variable "Cost" for each simulated airman in month t is initialized and is then recalculated monthly as a function of Tenure as "Cost=A328Cost(Tenure)." Thus, as Figure 5 shows, Cost in Month 0 is $2700, in Month 1 Cost is $2650, and so forth.

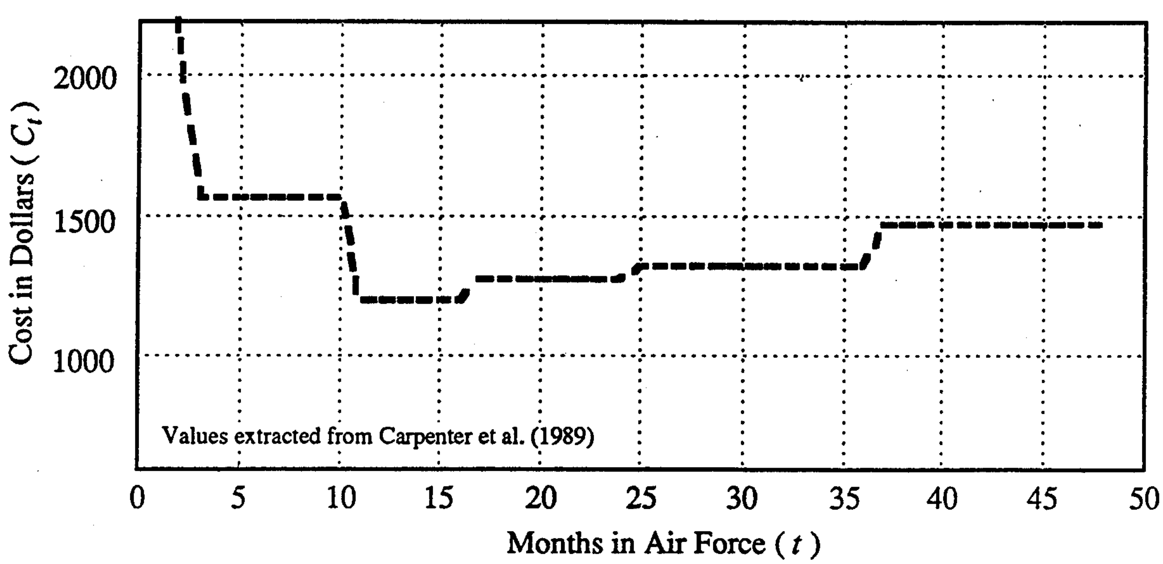


Figure 4: TTP Cost Model

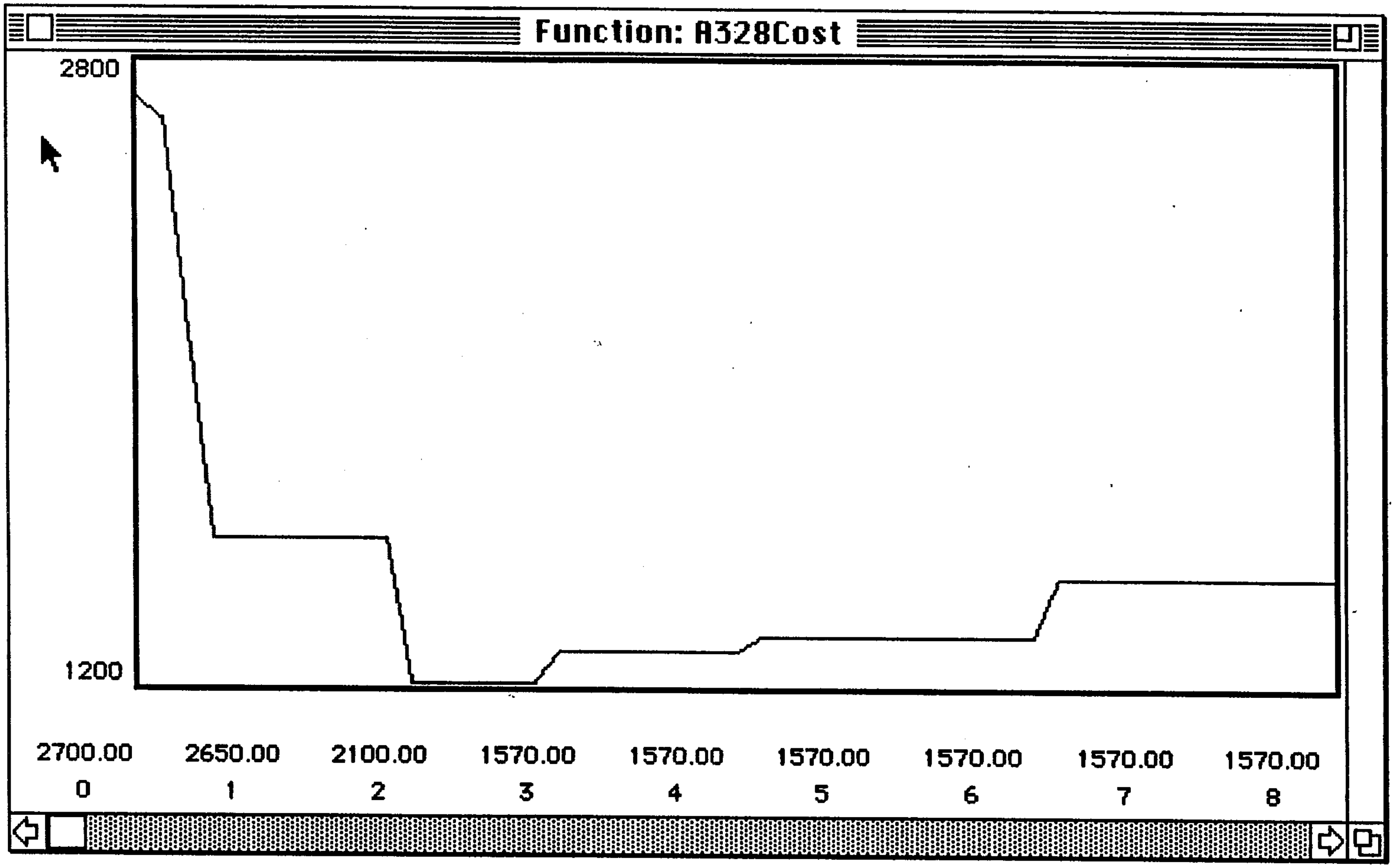


Figure 5: CSM Implementation of TTP Cost Model

TTP Productive Capacity Model. Carpenter et al. (1989) modeled productive capacity during the first term of enlistment after S-shaped learning curves which may be described generally as $y = 1/(1 + \exp(-x))$, or as the logistic function. More specifically, Carpenter et al. (1989) modeled first-term productive capacity as a function of tenure and cognitive ability as:

$$P = 1/(1 + \exp(-b_0 - b_1X_1 - b_2X_2)), \tag{7}$$

where P = productive capacity, X_1 = months of experience, X_2 = cognitive ability (ASVAB Electronics score), and b_0, b_1, and b_2 = parameters to be estimated. P was defined in terms of task performance time relative to fastest possible performance time as t^*/t, where t is an airman's observed performance time and t^* is the fastest possible performance time computed as one minute less than the minimum observed performance time (i.e., $t^* = \min(t) - 1$). Thus, P reflects the proportion of maximum productivity achieved by an individual.

Estimates for b_0, b_1, and b_2 were obtained by first re-expressing Equation 7 as:

$$\ln(P/(1-P)) = b_0 + b_1X_1 + b_2X_2 \tag{8}$$

and then using ordinary least squares (OLS) to estimate b_0, b_1, and b_2 from the regression of $\ln(P/(1-P))$ on experience (X_1) and ASVAB Electronics score (X_2).

Using this procedure, Carpenter et al. (1989) estimated productive capacity functions for 10 different task clusters for AFS 328x0 as well as an aggregate function across all tasks. Parameter estimates for the aggregate function were:

$$\ln(P/(1-P)) = -1.9945 + .0273X_1 + .0167X_2, \tag{9}$$

where all parameter estimates were statistically significant. Thus, the natural log of the ratio $P/(1-P)$ was estimated to be a linear function of months of experience and of aptitude.

CSM Productive Capacity Model. Implementation of the TTP Productive Capacity submodel into the CSM, with one exception, also was straightforward. Assuming that Carpenter et al.'s (1989) aggregate results for the Productive Capacity submodel are the most representative of those presented, Equation 7 and parameter estimates from Equation 9 were implemented to define productive capacity in the CSM. However, one complicating factor was that Carpenter et al. (1989) assumed that airmen would not be productive (i.e., productive capacity equals zero) as long as they are in training (10 months). Thus, productive capacity must only be defined for airmen who are tenured 11 months or longer (the assumed duration of recruitment and training). Thus, in the CSM, productive capacity was initialized to zero at the beginning of the simulation (ProdCap = 0), and was recalculated monthly according to:

$$\text{ProdCap} = (\text{Tenure}>=11)*(1/(1 + \exp(1.9945 - .0273*\text{Tenure} - .0167*\text{Electronics}))), \tag{10}$$

where the logical expression (Tenure >= 11) results in a nonzero value for Equation 10 only if simulated airmen have experience of at least 11 months (i.e., have graduated from training).

CSM Model Integration

The three component CSM models presented above as translations of the original TTP submodels were integrated into a single CSM in MPlanSim which is presented here as "TTP89." Figure 6 shows a flowchart depiction of the CSM.

Initially, simulated recruits enter the with zero Tenure and Productive Capacity, recruiting costs equal to $2,700, and with some Electronics score (E-Score) chosen randomly from an approximately normal distribution with the first four moments of the parent distribution shown in Figure 6. Recruits are then "selected" for the simulation based on their E-Score (a cutoff of 80 is shown in Figure 6), or are ignored. For those simulated airmen who are "selected", values of relevant variables are recalculated monthly. Specifically, the value of Tenure is incremented by 1 monthly, Cost is recalculated according to the function A328Cost described earlier and shown in Figure 5, productive capacity (PC) is recalculated according to Equation 10, and termination probability (TP) is calculated according to Equation 6. On the basis of their termination probabilities, some simulated airmen will be

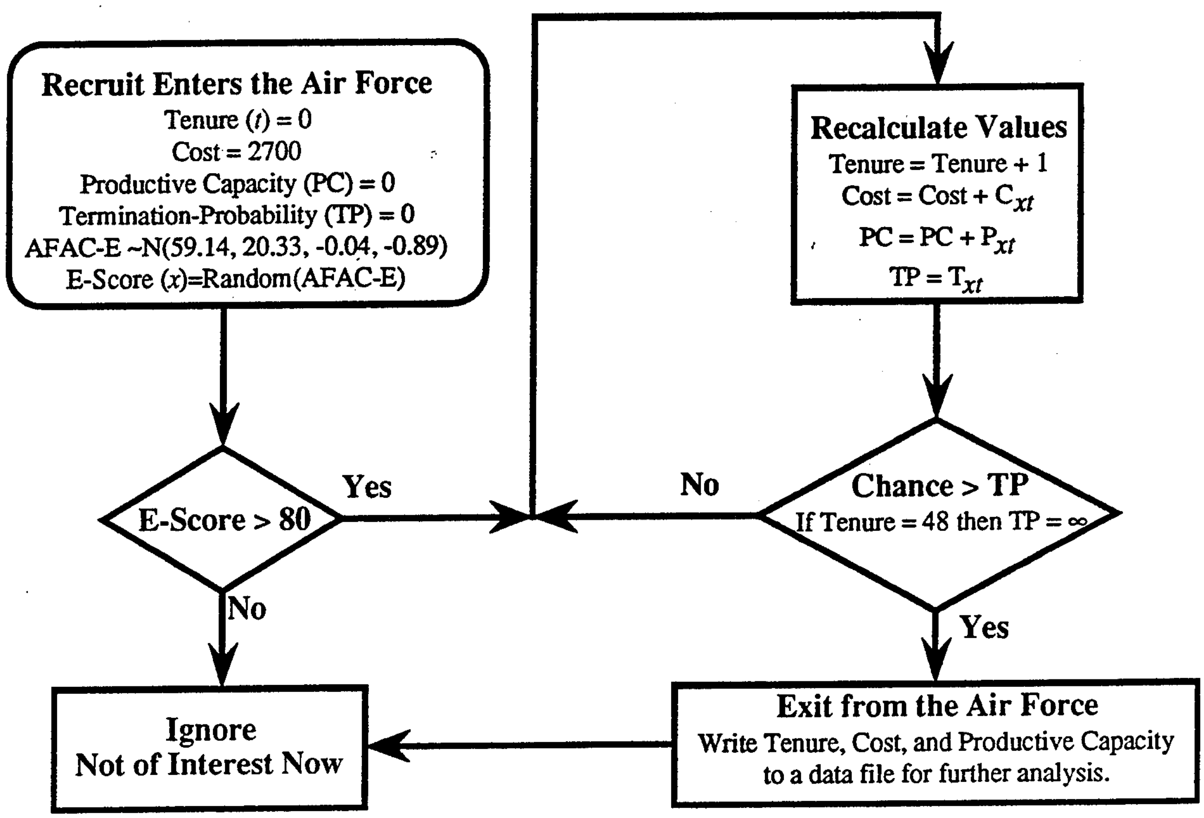


Figure 6: CSM Implementation of Employee Flows in TTP Model

exited from the simulation over the course of the first 47 months. For those exited from the system, current values of tenure, productive capacity, and costs are recorded for further summary analyses. Values on these variables are recalculated for those simulated airmen who remain in the system in the tth month until t = 48, at which time all airmen remaining in the system with Tenure = 48 months are exited from the system.

Figure 7 summarizes the MPlanSim implementation of the system depicted in Figure 6. The upper left-hand portion of Figure 7 shows that the CSM representation of the TTP model consists of three job states: Applicants, A328x0 incumbents, and an Exit state for simulated airmen who are exited from the system. Also shown here are the processes by which simulated persons are transitioned through the system: (a) A328x0 incumbents are first exited from the system on the basis of a conditional Markov process (M-1) defined earlier in terms of their termination probabilities (TP in Figure 6, or "QuitProb" in Figure 7 and Equation 6), (b) subsequently, a second conditional Markov process (M-2) "selects" simulated applicants into the A328x0 job state if their Electronics score is at least 80.

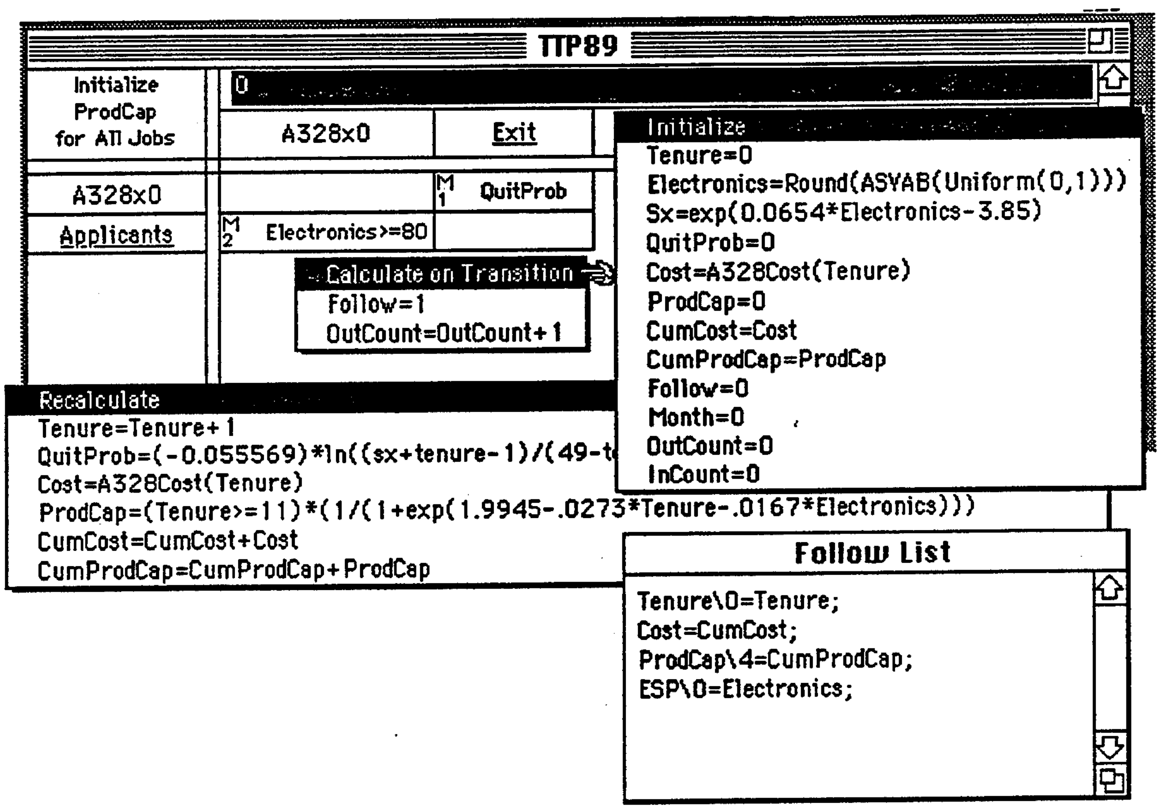


Figure 7: Summary of CSM Implementation of TTP Model

The top-right portion of Figure 7 ("Initialize" box) shows values to which variables were initialized. As discussed earlier, (a) Tenure, termination probability (QuitProb), and productive capacity (ProdCap) were all initially set to zero, (b) Electronics scores and the intermediate variable used in the calculation of QuitProb (Sx) were set to an initial value and were constant for the duration

of the simulation, and (c) Cost was determined from the function A328Cost (see Figure 5). In addition, (a) two variables that were defined to track cumulative costs and productive capacities (CumCost and CumProdCap, respectively) were initialized at the current Cost and ProdCap values, (b) values on four other variables that were defined to track individuals through the simulation and their exit from it (Month, Outcount, Incount, and Follow) were initialized at zero.

The lower left portion of Figure 7 ("Recalculate" box) shows recalculation formulae. Tenure is incremented monthly by 1, QuitProb and ProdCap are recalculated according Equations 6 and 10 respectively, and Cost is calculated from the function shown in Figure 5. The final two formulae show that CumCost and CumProdCap are recalculated monthly on the basis of their previous values plus the current values of Cost and ProdCap, respectively.

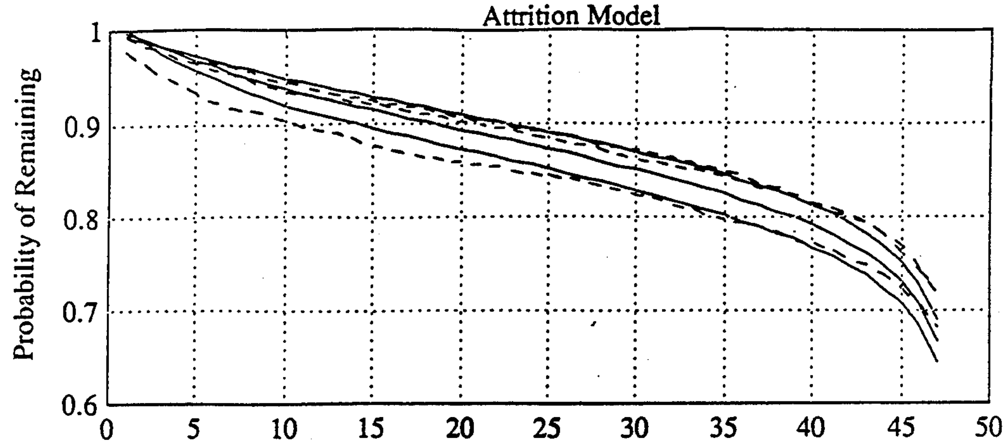
The center box in Figure 7 ("Calculate on Transition") shows that (a) the variable Follow is recalculated whenever a simulated individual transitions either from the Applicant state to A328x0 or from A328x0 to the Exit state, indicating that summary statistics are to be recorded for that individual, and (b) Outcount is recomputed by incrementing its value each time a simulated airman transitions from A328x0 to the Exit state.

Finally, the box in the lower right ("Follow List") indicates the variables whose summary statistics are to be recorded as controlled by the Follow variable. This box shows that each simulated airman's tenure, cumulative costs, cumulative productive capacity, and aptitude score were recorded as variables to "follow" and record for the purposes of computing descriptive statistics on those airmen still in the simulation and those that had been terminated at the end of the simulation.

CSM Results and Comparison With TTP Model

Attrition Submodel. Figure 8 shows results of the attrition portion of the CSM model in comparison with results presented previously by Carpenter et al. (1989). Results are evaluated at the midpoints of the top three Electronics deciles. TTP Model results were calculated from Equation 3, whereas MPlanSim results were calculated as the proportion of simulated airmen remaining in the system at the end of 48 months. For each aptitude group, the CSM using MPlanSim retained slightly more airmen than did the TTP model (up to 4 percentage points more). However, the root mean squared (RMS) differences between TTP and CSM results and their correlations across the 48 months indicated a close correspondence between the TTP Model's algebraic results and those estimated numerically on the basis of the CSM.

Cost Model. Figure 9 shows TTP versus MPlanSim comparative results for the cost submodel, again shown separately for the top three aptitude deciles. TTP Model results were calculated on the basis of formulae presented by Carpenter et al. (1989, p. 42) for the expected first-term cost for an individual conditional on aptitude level and probability of remaining in the Air Force. MPlanSim results were calculated by tracking costs cumulated for individuals remaining in the simulation on the basis of the CumCost variable discussed earlier. Results showed that MPlanSim results corresponded closely with algebraic TTP results, in one case slightly underestimating cumulative costs (by 0.8%) and slightly overestimating costs in the other two cases (by 0.16% and 1.2%). These results and the

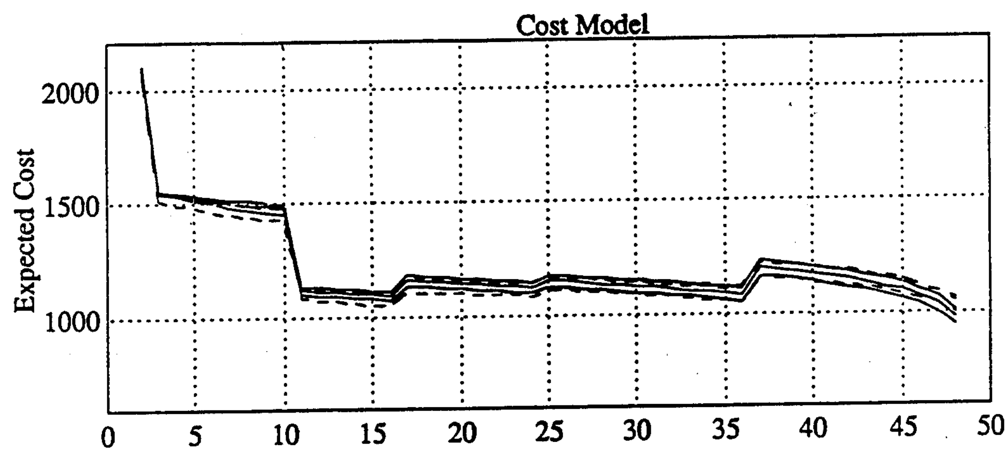


Expected Attrition Before End of Term

	75	85	95
TTP Model	0.6446	0.6685	0.6901
MPlanSim	0.6840	0.7153	0.7217
Difference	0.0394	0.0469	0.0316
RMS Difference	0.1058	0.1171	0.0449
Corr	0.9986	0.9997	0.9984

*E-Score = 75 85 95 TTP Model (solid) — MPlanSim (dashed)

Figure 8: Comparison of CSM vs. TTP Attrition Model Results



Overall Cost Estimates

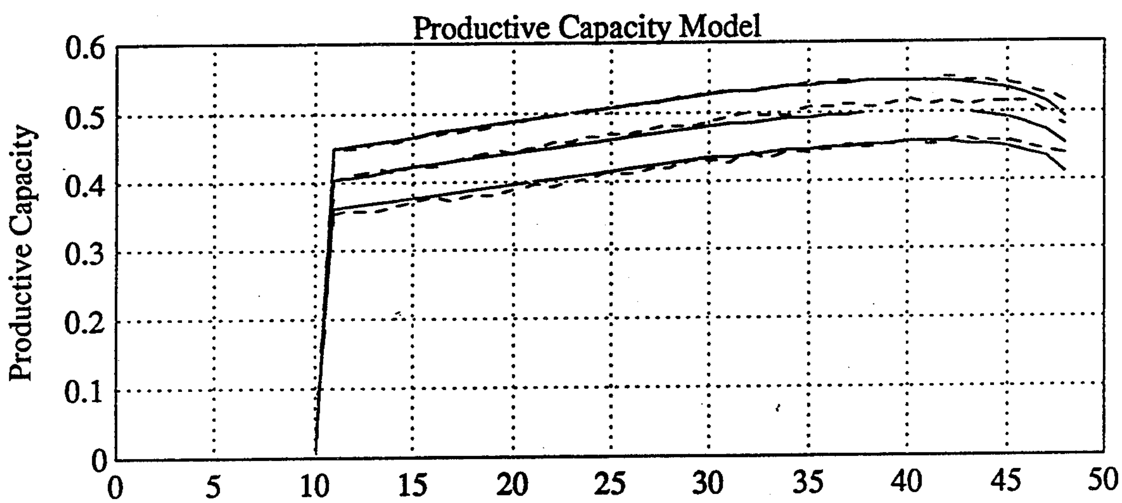
	75	85	95
TTP Model	61210.07	62445.73	63432.56
MPlanSim	60699.63	63205.12	63531.34
Difference	-510.44	759.39	98.78
RMS Difference	155.15	168.65	65.06
Corr	1.00	1.00	1.00

*E-Score = 75 85 95 TTP Model (solid) — MPlanSim (dashed)

Figure 9: Comparison of CSM vs. TTP Cost Model Results

essentially perfect correlation between monthly results across the first term again demonstrated close correspondence between the algebraic TTP results and the numeric CSM estimates.

Productive Capacity Submodel. Figure 10 compares TTP and MPlanSim results for the Productive Capacity submodel, again for midpoints of the top three aptitude deciles. TTP Model results were calculated on the basis of formulae presented by Carpenter et al. (1989, p. 38) for the expected first-term productive capacity for an individual conditional on aptitude level and probability of remaining in the Air Force. MPlanSim results were calculated by tracking productive capacity (ProdCap) cumulated for individuals remaining in the simulation on the basis of the CumProdCap variable discussed earlier. Results showed that MPlanSim slightly underestimated productive capacity in one case (by 0.05%) and slightly overestimated productive capacity in the other two cases (by 0.015% and 1.86%). These findings and the correlation of 1.00 between monthly results across the first term again demonstrated the high degree of correspondence between the algebraic results obtained from the TTP Model and the numeric estimates obtained using MPlanSim.



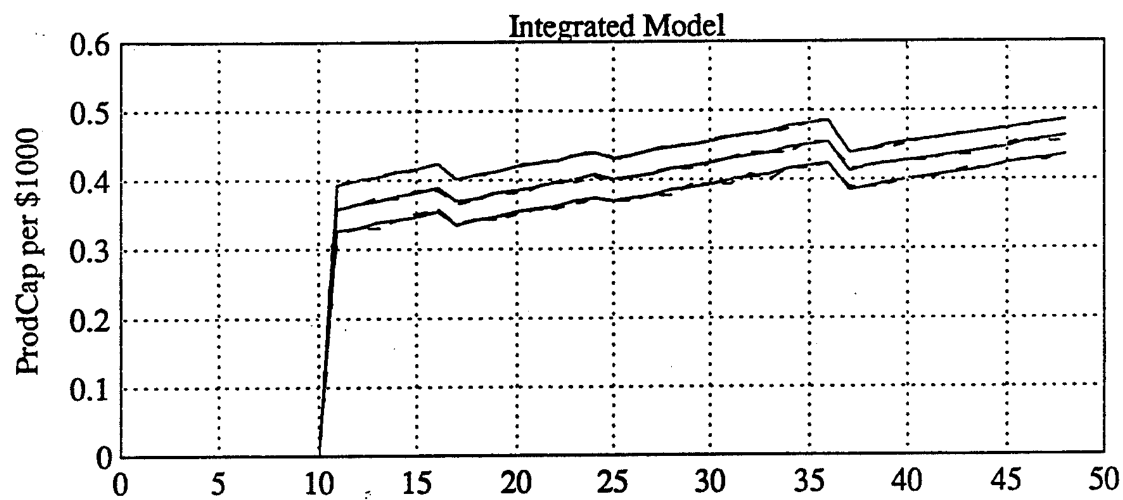
Overall Productive Capacity Estimates

	75	85	95
TTP Model	16.00	17.73	19.44
MPlanSim	15.92	18.06	19.48
Difference	-0.08	0.33	0.03
RMS Difference	0.05	0.07	0.03
Corr	1.00	1.00	1.00

*E-Score = 75 85 95 TTP Model (solid) — MPlanSim (dashed)

Figure 10: Comparison of CSM vs. TTP Productive Capacity Model Results

Integrated Model. Figure 11 plots results obtained from the integration of the Attrition, Cost, and Productive Capacity submodels and shows the monthly productive capacity obtained per $1,000 across the first term. The plot indicates that TTP and MPlanSim results are nearly identical. The similarity in results also can be seen in the tabled values for average productive capacity per $1,000 and the average cost per productive unit which are nearly identical for TTP versus MPlanSim results. Thus, whereas some slight discrepancies were noted earlier in comparisons between TTP and MPlanSim results for the Attrition, Cost, and Productive Capacity Submodels individually, these differences tended to cancel one another out in the integration of the three components so that overall results were essentially identical.



	Productive Capacity per $1000			Ave. Cost per Productive Unit		
	75	85	95	75	85	95
TTP Model	0.3036	0.3277	0.3515	3827	3521	3263
MPlanSim	0.3032	0.3273	0.3511	3813	3499	3262
Difference	-0.0004	-0.0004	-0.0004	-14	-22	-1
RMS Difference	0.0178	0.0163	0.0035			
Corr	0.9999	0.9999	1.0000			

*E-Score = 75 85 95 TTP Model (solid) — MPlanSim (dashed)

Figure 11: Comparison of CSM vs. TTP Integrated Model Results

Conclusions

The primary purpose of Study I was to establish the fidelity of a CSM approach to assessing utilities in a single-job system by comparing CSM results with algebraic results obtained previously by Carpenter et al. (1989). Results indicated that CSM findings closely paralleled algebraic results obtained earlier. Thus, these findings support the ideas that (a) traditional algebraic approaches to

utility assessment can be adapted for CSM of the same personnel systems, and (b) when properly implemented, simulation methods can closely replicate algebraic model results.

III. STUDY II: SIMULATION OF CLASSIFICATION DECISIONS IN AN INTERDEPENDENT MULTIPLE-JOB SYSTEM

One of the key conceptual limitations to traditional approaches for estimating the utility of a single HRM intervention in a single job is the implicit assumption that both the intervention (e.g., selection, training, turnover reduction strategy) and the job exist in a self-contained organizational context. That is, utilities of productivity-enhancing HRM programs have been assessed without regard to (a) interdependencies with other programs, or (b) direct or indirect effects on both the effectiveness and costs of other HRM programs. Similarly, assessing program utilities in jobs in isolation ignores effects that program implementation may have on HRM interventions in other jobs. For example, if only Job A is considered, determining that a test cutoff at the 80th percentile is optimal for test utility in Job A ignores the possibilities, as might be the case in personnel classification decisions, that (a) the same selectees may also be required in Job B, and (b) there are too few applicants in the applicant pool to adopt an 80th percentile cutoff for both Job A and Job B. As a second example, raising aptitude requirements for Job A may result in a substantial productivity payoff for Job A, but it may also significantly raise training costs or reduce productivity in other jobs which draw on the same applicants. These examples point to the need to estimate HRM program utilities within more realistic, interdependent organizational contexts.

The purposes of Study II were to (a) use CSM to develop procedures for evaluating the overall organizational payoffs of alternative personnel classification policies, (b) extend CSM of utilities in a single-job system to more complex multiple-job system, (c) assess interdependencies among payoff estimates in a multiple-job system, (d) investigate potential tradeoffs between single-job and overall personnel system utility, and (e) perform sensitivity analyses of the effects of changes in HRM policies on single-job and overall system payoffs.

Selection of AFSs

The current USAF enlisted structure contains over 300 separate career ladders or Air Force Specialties (AFR 39-1). However, we chose to limit the multiple-job simulations reported here to a much smaller work domain (a) so that information regarding employee characteristics and flows across relevant job states could be obtained from available personnel data, (b) so that the modeled system and simulation results could be clearly communicated, and (c) because required data on relationships between job performance and aptitude and experience were available for a relatively small subset of AFSs. Specifically, we chose one AFS from each of the MAGE aptitude areas that had been studied previously as part of the Joint Service Job Performance Measurement (JPM) Project. These four AFSs were Air Traffic Control Operator (AFS 272x0, now 1C1x1), Avionics Communication Specialist (AFS 328x0, now 2A1x2), Aerospace Ground Equipment Mechanic (AFS 423x5, now AFS 2A6x2), and Personnel Specialist (AFS 732x0, now 3S0x1).

General Structure of the Simulated Multiple-Job System

There are many ways in which enlisted airmen (a) enter the USAF (e.g., through the Guaranteed Training Enlistment Program or accession into basic military training followed by classification into an AFS), (b) move or transfer across different positions (e.g., graduation vs. elimination from basic and resident technical training, cross-AFS retraining), and then (c) leave the USAF (e.g., early-outs, attrition due to substandard performance or personal reasons, completion of a single term of enlistment, retirement of career airmen, etc.). Modeling all possible transitions of airmen into, through, and out of service to the USAF was beyond the scope of the present work. Rather, we attempted to simulate the most typical employee flows in the four-AFS system defined for the simulation.

Simulated Job States

A very broad overview of this system is shown in Figure 12, which also identifies many of the job states that were defined for the multiple-AFS simulations. For these simulations, it was assumed that new Recruits are selected from an applicant population, and that all new Recruits then enter basic military training (BMT). Some basic airmen are eliminated from BMT. Those that remain (BMT graduates) are classified according to their personal characteristics and AFS requirements into one of four AFSs. Once classified, recruits undergo some period of resident technical training (RTT, shown as the four "Tech" cells in Figure 12), during which time some airmen are eliminated as well. Those remaining are graduated to incumbency (3- and then 5-skill level) in the four AFSs chosen for study (AFSs 272x0, 328x0, 423x5 and 732x0). Some incumbents terminate during the course of the first term of enlistment and, for the purpose of the simulation, all incumbents remaining at the end of 48 months were terminated since we focused exclusively on first-term airmen. Thus, although this job system ignores other employee flows that occur, such as guaranteed job placement prior to BMT, and cross-AFS retraining during the first term, it does represent the most typical accession-incumbency-termination scenario for first-term enlistees.

Implementation in MPlanSim. Multiple-job simulations were developed around the general personnel flows shown in Figure 12 using MPlanSim (Ladd & Kudisch, 1994). The overall structure of the simulation is a matrix of transitions defined on the y-axis by job states (i.e., simulated organizational positions) from which simulated individuals move (or transition) into other job states, that are defined on the X-axis. The structure of these job states as implemented in the MPlanSim model developed here is summarized in Figure 13. The Ms and Xs in Figure 13 indicate the transitions implemented in the CSMs that correspond to the movements depicted by arrows in Figure 12. The Ms indicate Markov transition processes and the Xs indicate various types of transitions (e.g., selection, placement, optimized placement) that were the manipulations carried out in the simulations reported here. The numbers coinciding with the Ms and Xs indicate the evaluation orders, or the order in which the transitions were effected in the simulations (e.g., individuals were first transitioned from AFS732x0 to the Exit state according to a Markov process (M1); next, individuals were transitioned from AFS423x5 to the Exit state (M2), etc.).

Along the left of Figure 13, the applicant pool is represented as an "Applicant" job state called "Recruits." The second job state ("USAF-Qualified") is shown in italics because it is a "Temporary Job State" used to select Recruits according to qualifying standards discussed later. Next, the job state

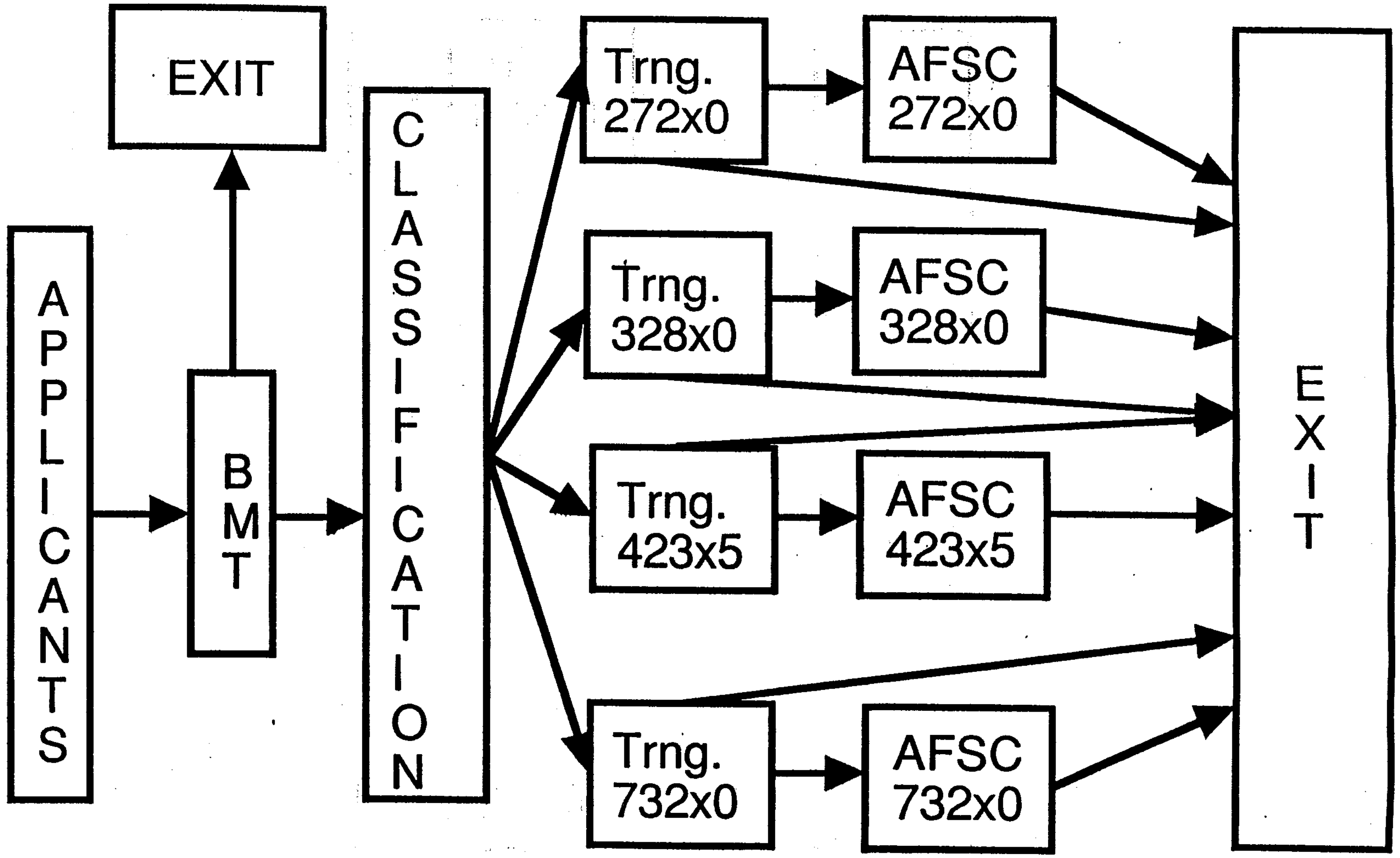


Figure 12: Multiple Job System

of basic military training is referred to as "BMT." The job state "Classification" also is a "Temporary Job State" which was used to effect personnel assignments. Resident Technical Training (RTT) job states for each of the AFSs appear next (e.g., Tech272x0), followed by job states referring to incumbency status (e.g., AFS272x0).

The remaining job states shown along the top of Figure 13 ("Other AFS," "Attrition," and "Exit") are "Termination Job States," or job states into which individuals are transitioned once they are exited from the simulation. Each of these is discussed in greater detail later.

Once these job states were defined, several other characteristics of the model had to be specified which concerned (a) the variables that were to be created, recalculated, and summarized as part of the simulation. These included such factors as airman aptitude, experience (tenure), performance, costs, and job state service times, and (b) the rules governing employee flows or transitions across job states, including airman selection, classification, graduation, and elimination.

Variables

Many variables were defined for the model, including characteristics of simulated individuals (Person Variables), job states (Job Variables), and the system as a whole (Global Variables). Table 2 lists the key Person-, Job-, and Global-level variables' names, methods of initialization and recalculation, along with brief descriptions. The "Initialize" column in Table 2 indicates whether each variable's values were set intially (a) upon an individual's entry into the simulation ("Upon Entry"), (b) upon an individual's transition from one job state into another ("On Transition"), or (c) at the very beginning of the simulation ("Startup"). The "Recalculate" column indicates whether each variable's values were (a) recalculated monthly as a function of system characteristics ("Monthly"), or (b) remained fixed after initialization ("Fixed"). Detailed descriptions of the initialization and recalculation formulae for all variables are included in Appendix A.

Four general categories of Individual- or Person-level variables were defined relating to aptitude, experience (tenure), performance, and costs. First, all individuals created for the simulations were assigned five aptitude scores (AFQT and MAGE composite percentile scores) according to population distribution characteristics and the correlational structure described by Maier and Sims (1986). These were used to determine whether applicants met minimal USAF aptitude cutoffs, for selection/classification decisions, and to determine termination probabilities and simulated performance levels. Second, "TAFMS" tracked individuals' total tenure in the simulation, while "TimeInJob" tracked individuals' tenure within particular job states. These variables were used to determine individuals' termination probabilities and simulated performance levels. Third, three performance-related variables were defined: (a) a regression-based predicted performance level ("PredPerf") that was used in some of the selection/classification models described later, (b) "Performance," or individual productive capacity, which was determined on the basis of functional relationships estimated between hands-on performance scores and aptitude and experience determinants from JPM data, and (c) "CumPerf," a summation of individual performance across months for individuals in the simulation. Finally, salary ("Pay") and indirect costs ("IndirectCost")

	USAF Qualified	BMT	*Classification*	Tech 272X0	Tech 328X0	Tech 423X5	Tech 732X0	AFS 272X0	AFS 328X0	AFS 423X5	AFS 732X0	Othe r AFS	Attrition	Exit
Recruits	M24													
USAF Qualified		X25												
BMT			X18									M23	M14	
Classification				X19	X20	X21	X22							
Tech 272X0								M17					M13	
Tech 328X0									M16				M12	
Tech 423X5										M15			M11	
Tech 732X0											M9		M10	
AFS 272X0													M8	M4
AFS 328X0													M7	M3
AFS 423X5													M6	M2
AFS 732X0													M5	M1

Figure 13: Summary Transition Matrix for Multiple Job System

were estimated from data presented in Air Training Command Cost Factors Manual (1992) and were cumulated over each individual's total length of service ("CumCost").

Table 2.

Multiple Job Simulation Variables

Variable	Initialize	Recalculate	Description
Person-Level:			
ID	Upon Entry	Fixed	Δ Simulated individuals'
AFQT	Upon Entry	Fixed	Individuals' AFQT
M,A,G,E	Upon Entry	Fixed	Individuals'Mechanical, Administrative, General and Electronics percentile scores.
TAFMS	Upon Entry	Monthly	Total Active Federal Military Service, or global tenure in the simulation.
Time in Job	On Transition	Monthly	Tenure in current job state.
QuitProb	On Transition	Monthly	Probability of termination from current job state.
PredPerf	Upon Entry	Fixed	Predicted performance level based on MAGE and AFQT
Perform	Upon Entry	Monthly	Simulated Productive Capacity based on TAFMS, MAGE and AFQT.
CumPerf	Upon Entry	Monthly	Cumulative Productive Capacity across total length of service.
Pay	Upon Entry	Monthly	Individuals' monthly salary plus benefits
Indirect Cost	Upon Entry	Fixed	Monthly indirect costs

Cost	Upon Entry	Monthly	Pay + Indirect Costs
CumCost	Upon Entry	Monthly	Cumulative costs across total length of service.
Job-Level:			
Job	On Transition	Fixed	Cardinal identification number for each job state.
Staff/ Level	Startup	Fixed	Desired staffing levels (numbers of airmen) for each job state.
Staff/ Size	Startup	Monthly	Actual current staff level for each job state.
Srv/ Length	Startup	Fixed	Monthly duration (time spent in residence) for each job state.
Mths/ Need	Startup	Monthly	Forecasted manpower needs for Tech Training job states.
BMTNeed	Startup	Monthly	Forecasted manpower need for BMT job state.
Global-Level:			
Month	Startup	Monthly	Current simulation month.

Major job-level variables included the number of individuals desired in each simulated job state ("StaffLevel") which reflected the existing populations (historically) of the jobs simulated, the actual number of individuals residing in each job state in a given simulation month ("StaffSize"), the maximum number of months that individuals could reside in each job state or its service length ("SrvLength"), and two variables that served to project future manpower needs for the Tech Training and BMT job states ("MthsNeed" and BMTNeed," respectively). StaffLevels for the multiple-job simulations were determined using a complicated dynamic manpower planning system described in Appendix B.

Only one global-level variable was defined which tracked the current simulation time period ("Month").

Transitions - Employee Flows

Once the relevant job states, and individual-, job-, and global-level variables were defined, rules governing movement across the job states were specified. Four categories of transitions were defined: (a) terminations from various job states, (b) graduation from RTT to incumbency, (c) entrance into an AFS track following graduation from BMT, and (d) accession into the USAF from the applicant population.

Terminations. One way in which individuals were transitioned was to exit them from the simulation. Figure 14 summarizes the termination rules governing exit from each of the job states from which individuals could be transitioned ("BMT" through "AFS732x0" on the left-hand side of Figure 18) into three termination job states ("Other AFS," "Attrition," and "Exit"). The first four transitions effected in the model (M1 through M4 in Figure 18), exited individuals from the system who had completed their first term of enlistment. This was done by transitioning individuals from the four incumbency job states (AFS272x0 through AFS732x0) into the Exit job state unconditionally (i.e., with a probability of 1.00) if their TAFMS was greater than 48 months.

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	AFS423x5	AFS732x0	OtherAFS	Attrition	Exit
Recruits					
USAFQualified					
BMT			M23 TimeInJob>=2	M14 QuitProb	
Classification					
Tech272x0				M13 QuitProb	
Tech328x0				M12 QuitProb	
Tech423x5	M15 TimeInJob>=4			M11 QuitProb	
Tech732x0		M9 TimeInJob>=1		M10 QuitProb	
AFS272x0				M8 QuitProb	M4 TAFMS>48
AFS328x0				M7 QuitProb	M3 TAFMS>48
AFS423x5				M6 QuitProb	M2 TAFMS>48
AFS732x0				M5 QuitProb	M1 TAFMS>48

MPlanSim

Figure 14: Terminations

Some incumbents also were terminated from AFS, Tech, and BMT job states prior to the completion of their first term of enlistment. These terminations were governed by "QuitProb" values defined separately for each job state as a function of individuals' aptitude and experience levels. A detailed description of the initialization and recalculation formulae for "QuitProb" values is given in Appendix C.

Finally, individuals were moved from BMT into a third exit state called "OtherAFS." The purpose of this transition was to relocate individuals who had not otherwise been eliminated from BMT and who also had not been transitioned into one of the four AFSs. This could occur if, for example, a greater number of individuals were graduated from BMT than there were open slots in the Tech job states, or if simulated individuals' aptitude levels failed to qualify them for any of the AFSs.

Graduations. After terminations were effected, individuals were "graduated" from the Tech job states (e.g., Tech272x0) to incumbency (e.g., AFS272x0). The rules governing these transitions were simple. All individuals who had not been eliminated from RTT previously and whose service time in one of the Tech job states was greater than or equal to the service length of the Tech job state were tansitioned into incumbency (AFS272x0 through AFS732x0). Thus, individual "graduation" was a function of residing in a Tech job state for the duration of the simulated training period and having not been otherwise eliminated.

Graduation from BMT (M18) was governed in a similar manner. All individuals who had not been otherwise eliminated from BMT and whose job service time was greater than or equal to the length of BMT (2 months) were graduated into "Classification".

The remaining transitions involved selection among Recruits into the USAF on the basis of minimun aptitude qualifications and placement or classification into career tracks.

Selection/Accession

The selection/accession decision rule was the same in all simulations. Applicants ("Recruits") were selected if their aptitude scores met (a) minimum USAF-wide qualifications, and (b) the minimum MAGE percentile cutoff for at least one of the four AFSs. This was implemented according to the following equation:

$$(AFQT>=21)\&(G>=45)\&((M+A+G+E)>185)\&$$
$$[(G>48)|(E>53)|((M>50)\&(E>46))|(A>48)]. \tag{10}$$

The first part of Equation 10 requires that in order to be selected (i.e., become "USAFQualified"), an airman must have a minimum AFQT percentile score of 21 and a minimum G percentile score of 45 and a minimum combined MAGE percentile score of 185[1]. In addition, a selectee must either meet the minimum G percentile score for AFS272x0 (G > 48) or the minimum E percentile score for AFS328x0 (E > 50), or the combined minimum M and E scores for AFS423x5 ((M > 50) and (E > 46), or the minimum A cutoff for AFS732x0 (A > 48). Thus, this rule was designed to select

[1] As of September 1995, the Air Force no longer uses the sum of MAGE.

simulated airmen who met both minimum USAF aptitude requirements and the minimum aptitude cutoff for at least one of the AFSs under study. In effect, these requirements reduced the applicant pool by almost exactly half. A selection ratio of 2.273 was employed to reflect a previous USAF practice of selecting approximately 44% of the applicant pool. Also, in order to maintain an adequate supply of airmen for the simulation, 110% of the anticipated manpower need was selected for the simulation.

Selection was from the "Recruit" job state into the temporary "USAFQualified" job state. From the "USAFQualified" job state, simulated airmen were selected top-down on the basis of AFQT into BMT. Individuals were transitioned into "OtherAFS" if they were not selected for BMT. Thus, "excess" individuals were effectively eliminated from the simulation.

Individuals who were selected for BMT either were terminated subsequently, or resided there for 2 months. All airmen who were not eliminated were graduated from BMT into a second temporary job state ("Classification") from which they were assigned to one of the four Tech Training job states and eventually into the respective AFS job state (if they were not eliminated from RTT). Variations in the Classification decision rules constituted the manipulations performed in the simulations reported here.

Classification

Classification decisions in the simulations were based on four different classification algorithms: (a) random assignment, (b) top-down selection, (c) placement, and (d) optimized placement.

Random assignment was accomplished by transitioning simulated airmen from the temporary "Classification" job state into one of the Tech job states where they were assigned a uniform random number and where selection proceeded top-down on the basis of the random number. Remaining airmen reverted to the temporary "Classification" job state and into the next Tech job state where they were once again selected top-down on a newly assigned random number. This process continued until all Tech job states' manpower needs were filled, after which any remaining simulated airmen were transitioned into the "OtherAFS" job state.

Top-Down selection decisions were effected by rank-ordering simulated airmen according to the AFS-appropriate MAGE composite score and selecting, on a top-down basis (i.e., highest scorer first, etc.), as many individuals as were needed to meet current manpower needs.

Placement decision rules were effected using either standardized MAGE composite scores or predicted performance levels ("PredPerf," see Appendix A). From the Classification temporary job state, all airmen were initially placed into the "OtherAFS" job state. Next, airmen were considered for movement from the OtherAFS job state into each of the Tech job states. If the Tech job states were not staffed to their desired manpower levels an airman was transitioned into one of the Tech job states if his criterion score (i.e., MAGE composite score or predicted Performance score) was higher for the new job state than for the old job state. If the desired Tech manpower levels were already met, an airman was transitioned into a Tech job state only if his criterion score was greater than the lowest

criterion score already in the job state, and his score was higher for the new job state than the current job state, in which case a previously placed airman was displaced and then reclassified. The net result of this algorithm was to place each individual into the Tech job state associated with his highest standardized criterion score and to maximize Performance job-wise.

Optimized placement began with the Placement procedure, but performance was optimized system-wide using a simplified Ford-Fulkerson algorithm (Ford & Fulkerson, 1956). Specifically, a global performance criterion was defined as the total predicted performance across the four AFSs studied. This global criterion was optimized after initial placements by conducting pairwise comparisons among all airmen to be classified, and determining whether the overall system-wide criterion would be improved if any two airmen exchanged jobs. This search and exchange process iterated until no further exchanges could be identified which would improve overall predicted performance. Thus, optimized placement began with simple placement followed by interatively exchanging airmen among jobs until no further improvement in overall predicted performance could be made on the basis of additional exchanges.

The simulation experiments we conducted examined the effects of variations in these classification decision rules on staffing levels, costs, and productivity.

In Model 1, airmen were transitioned randomly from BMT into the four different Tech job states (and consequently into the respective AFS job states). In this model, all simulated airmen met minimum USAF aptitude requirements and also met the minimum aptitude cutoffs of at least one of the four AFS's. However, Model 1 provided for no differential selection or classification based on matches between simulated airmen's particular strengths and the aptitude requirements of the AFSs. We refer to this as a "baseline" or "reference" model against which the results for all other models were compared.

Model 2 used top-down selection on the basis of Electronic percentile scores for the Tech328x0 job state, and random selection for the remaining three AFSs. The rationale for this model was to simulate the effects that implementing a selection system in one job, but not others in an interdependent multiple-job system, would have for the job in which the system was implemented, versus the other jobs and for the system as a whole. Thus, we anticipated tradeoffs ignored by more traditional approaches to utility analysis, between optimizing outcomes in one of several interdependent jobs at the expense of these outcomes in other jobs, and possibly system-wide.

In Model 3 airmen were placed into the four Tech job states on the basis of AFS-appropriate MAGE composites. Model 3 was designed to simulate the situation in which (subject to staffing level constraints) each airman is placed into the Tech job state for which they have the highest standardized MAGE composite score. Thus, Model 3 attempted to maximize the "fit" between airman qualifications and job requirements by placing each airman into the job for which they had the highest standardized selector aptitude index. Consequently, we anticipated improvements in overall system performance for Model 3 as compared to random classification (Model 1) as well as the model that emphasized performance in only one job (Model 2).

Model 4 placed airmen from BMT into the four Tech job states on the basis of MAGE scores (as in Model 3), but placement was optimized system-wide. Like Model 3, Model 4 transitioned airmen on the basis of MAGE scores, but optimized placement on the basis of overall predicted system-level performance rather than on the match between individuals' qualifications and the jobs' requirements. Thus, we anticipated further improvements in overall system-level performance of Model 4 over Model 3 as predicted overall system performance was being optimized explicitly.

As in Model 3, Model 5 used a placement algorithm to transition airmen from BMT to the Tech job states, but on the basis of standardized predicted performance (i.e., "PredPerf," see Appendix A). That is, placement decisions were based on criteria representing performance predicted on the basis of the MAGE composites and AFQT scores rather than on the basis of standardized AFS-appropriate aptitude indexes. Thus, we anticipated some improvements in overall system performance of Model 5 as compared to Model 3 and substantial improvements over the random placement model (Model 1).

Finally, Model 6 classified airmen from BMT to the Tech job states using optimized placement based on standardized predicted performance for the four AFS jobs. Thus, we anticipated further improvements in overall system performance of Model 6 over Model 5, and again, substantial improvements over the random selection Model (Model 1).

In summary, Model 1 served as a baseline (random classification) model against which the effectiveness of all other models' selection, placement, or classification policies were evaluated. Model 2 simulated the situation in which a top-down selection system was implemented in only one of several interdependent jobs. Models 3 and 4 simulated placement and optimized placement of individuals based on MAGE composites, respectively. Thus, these two models reflected, in part, current USAF classification policy based on MAGE composites. Models 5 and 6 simulated alternative placement and optimized placement policies, respectively, based on simulated individuals' standardized job performance scores predicted on the basis of MAGE composites and AFQT scores.

Running the Simulations

Initially, each model was run for 48 Months in order to fully populate all job states and to exit the first cohort of individuals out of the system after their first term of enlistment. Next, the model was run an additional 12 months, during which time the stability of the model was evaluated. Finally, each model was run for another 48 months to evaluate the behavior of the models. Several summary dependent variables were tracked over the course of the simulations to evaluate model stability, and in later stages of the simulations, to evaluate the effects of variations in classification policy. These variables are listed and defined in Table 3. Broadly, these variables related to (a) the numbers of individuals residing in various simulated job states (Trng. Class Size and AFS StaffSize) (b) costs (Trng. Cost, AFS Cost, and Total Cost), (c) productivity (Total Production), and (d) overall system performance (Prod/Airman, Cost/Position, and Cost/Prod).

Start-up and Stability of the Models

Figure 15 plots StaffSizes (i.e., numbers of individuals in the simulation) for the AFS job states for the first 108 Months of the simulation for Model 1, the baseline model (i.e., 48 Months start-up plus a 60-month stabilization period). The lower-left hand portion of Figure 15 shows that AFSs' StaffSizes began to grow at different times during the start-up due to differences in Tech training

Table 3.

Simulation Summary Dependent Variables

Variable	Description
Trng. Class Size	Average number of airmen in a given AFS's Tech job state (including 1st, 2nd, 3rd, etc. month trainees as appropriate)
AFS Staff Size	Average number of airmen in respective AFS job states
Trng. Cost($k)	Average total recruitment and training costs, including acquisition costs, BMT costs, Tech training costs, indirect costs and pay (in thousands)
AFS Cost($k)	Average total pay and indirect costs associated with respective AFS job states (in thousands)
Total Cost($k)	Sum of Trng. Costs and AFS Costs (in thousands)
Total Production	Sum of all Productive Capacity for all airmen in the respective AFS job states
Prod/Airman	Average Productive Capacity per airman in the respective AFS job state, or Total Production/AFS StaffSize
Cost/Position	Average Total cost per job state, or Total Cost/StaffLevel for respective AFS job states
Cost/Prod	Cost to procur unit Productive Capacity, orTotal Cost/Total Production

lengths (e.g., 1 month for AFS732x0 vs. 4 months for AFS328x0, see Appendix B). Continuing through Month 48, the growth in AFSs' StaffSizes reflects the gradual population of the jobs during the start-up phase. After month 48, AFSs' StaffSizes fluctuate in the neighborhood of the desired StaffLevels due to monthly variations in attrition in the AFS and Tech job states. Thus, Figure 15 shows graphically that the manpower planning system implemented in the simulations was efficient in maintaining StaffSizes at or near the desired staffing levels.

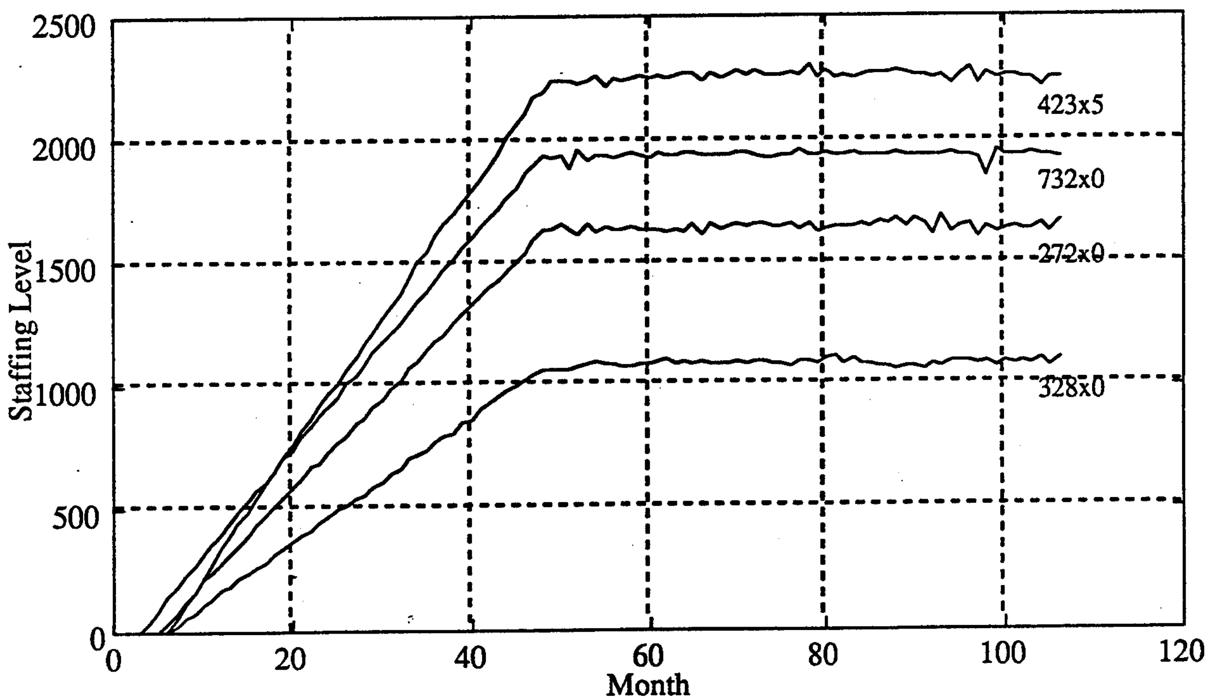

Figure 15: Model 1 Multiple Job System StaffSizes

Figure 16 plots Total Costs per month by AFS. Again, the increases in costs through month 48 reflect the start-up phase of the simulation, or the gradual population of the AFS job states. Note that costs also fluctuated monthly, mainly due to monthly variations in attrition in the Tech job states. These fluctuations were most notable in the AFS732x0 job. This was because the duration of Tech training was only one month. Thus, changes in Tech training StaffSizes were more volitile on a monthly basis for AFS732x0 (due to effects of random shocks in the simulation) than for the other AFSs where Tech training lasted for up to 4 months. Nevertheless, costs in all AFSs appeared to follow a stationary process following start-up, that is, no systematic increases or decreases in costs were observed following the 48th month.

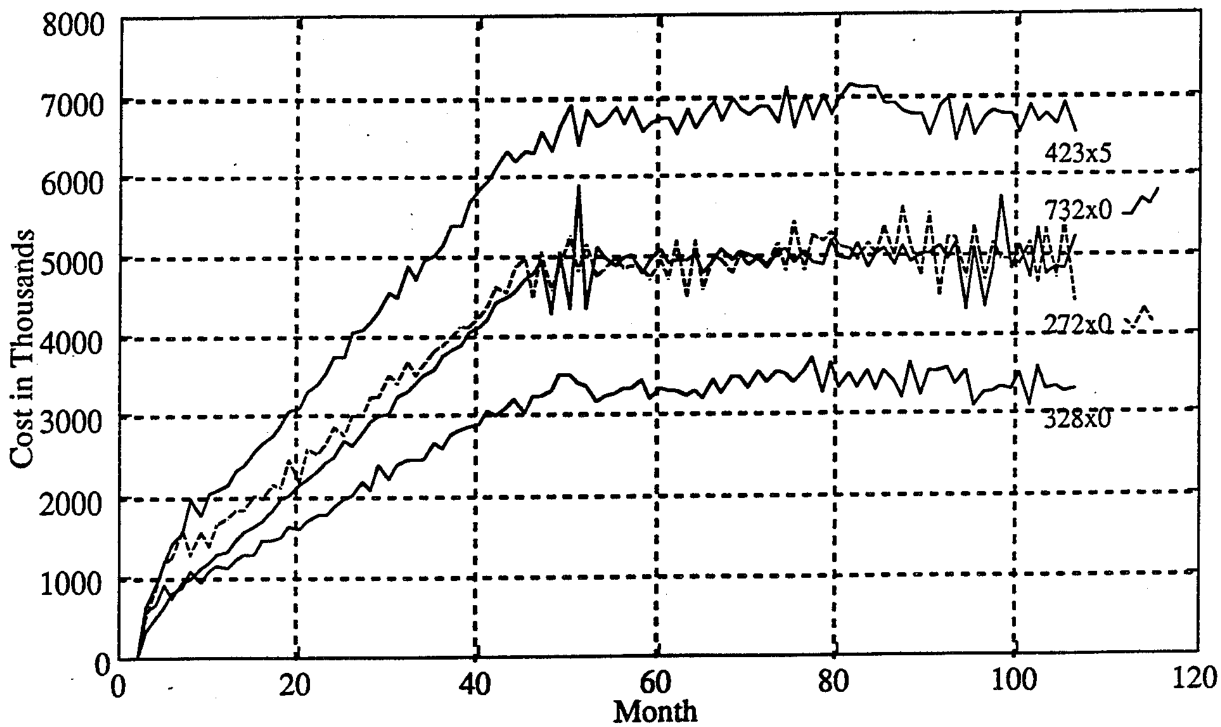

Figure 16: Model 1 Multiple Job System Total Costs

Figure 17 plots Total Production in the four AFSs as a function of month of the simulation. Again, the effect of the start-up phase was seen in the gradual increase in Production up through the 48th month, after which there is some stochastic variation around a stable mean Total Production for each AFS.

Finally, Figure 18 plots Total Production divided by StaffSize or mean Prod/Airman (i.e., mean productive capacity) across simulation months by AFS. This plot too shows that productive capacity reached reasonably stable values following the initial 48-month start-up period of the simulation.

Effects of Variations in Classification Policies

Table 4 shows the average monthly results for Model 1 (the baseline, or random classfication model), summarized over the last 48 months of the simulation period. The dependent variables listed were defined earlier in Table 3. Several results in the first four columns (i.e., for the four AFS job states) were noteworthy. First, mean AFS StaffSizes were very close to the desired StaffLevels

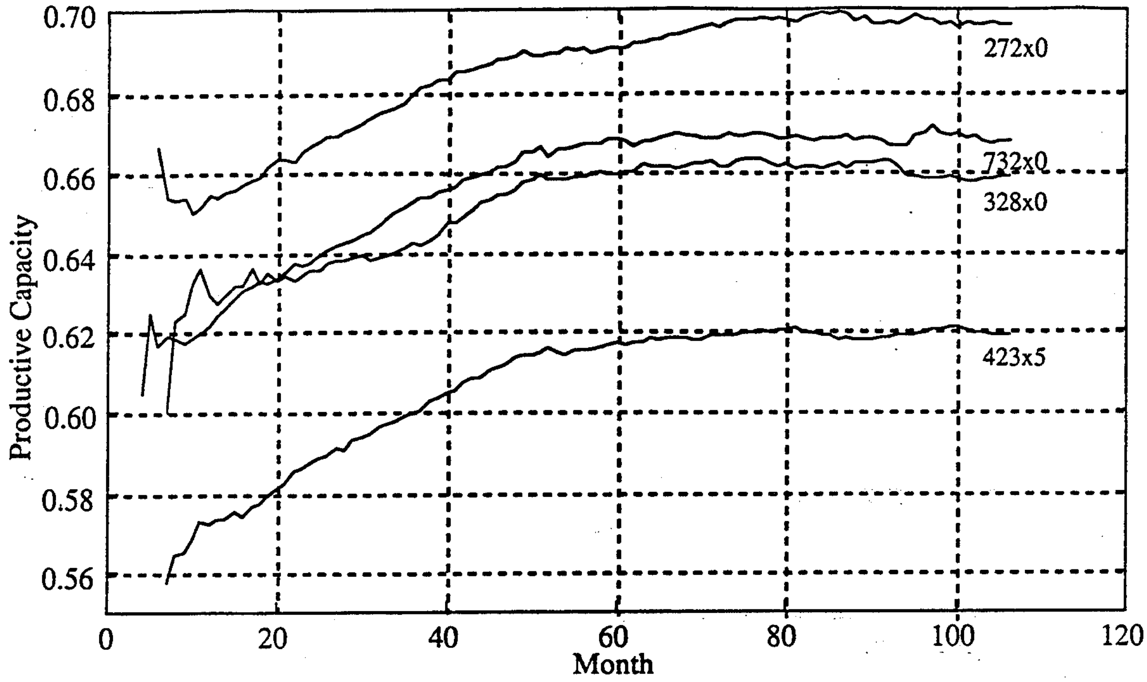

Figure 18: Model 1 Multiple Job System Mean Production/Airman

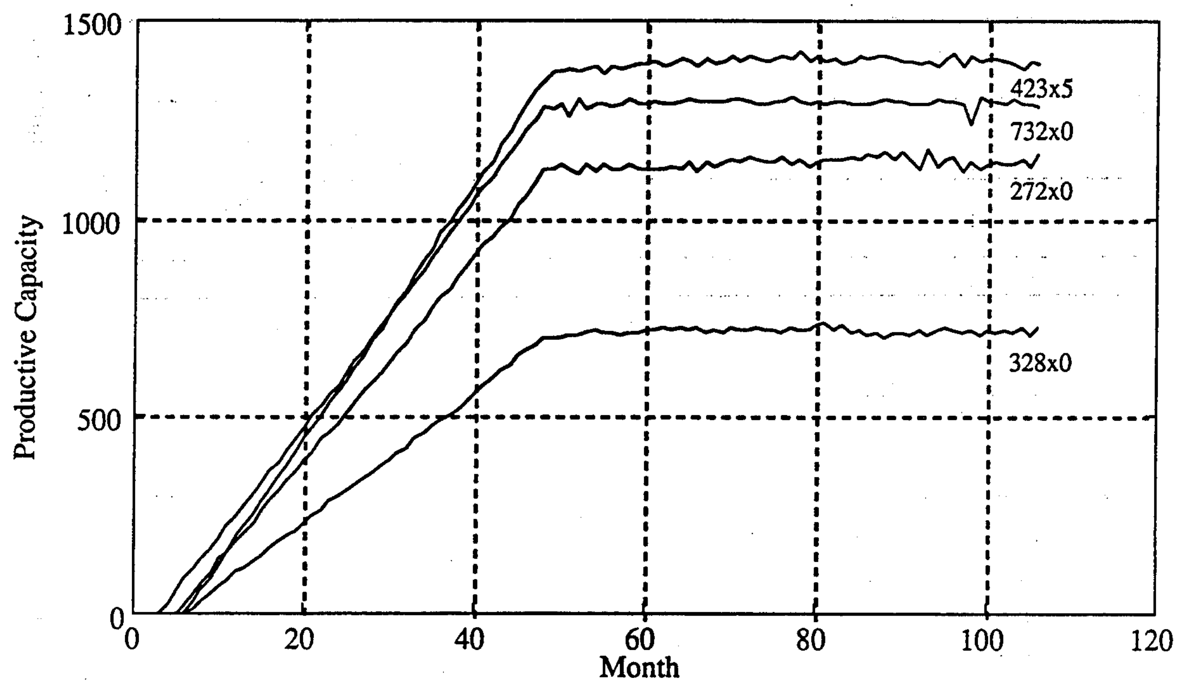

Figure 17: Model 1 Multiple Job System Total Production

(see Appendix B), with AFS272x0 being slightly overpopulated (100.4% of StaffLevel) and AFS 423x5 slightly underpopulated (99.6% of StaffLevel). Total Production in Table 4 is the mean monthly summation of all simulated individuals' productive capacity in the respective AFS job states, and

Table 4.

Model 1 Results

	AFS					
	272x0	328x0	423x5	732x0	Other	Overall
Trng. Class Size	147	125	254	49	6	581
AFS StaffSize	1644	1085	2262	1937	58	6987
Trng. Cost($k)	1305	918	1672	645	4	4545
AFS Cost($k)	3671	2452	5130	4304	397	15954
Total Cost($k)	4976	3370	6803	4949	0	20098
Total Production	1141	718	1405	1295	0	4558
Prod/Airman	0.696	0.661	0.619	0.668	0	0.652
Cost/Position	3038	3103	2997	2555	0	2900
Cost/Prod	4359	4697	4846	3824	0	17726

Note. Trng. Class Size = Tech job states' StaffSizes, AFS Staffsize = AFS job states' StaffSizes, Trng. Cost($k) = mean monthly total training costs for Tech job states in thousands, AFS Cost($k) = mean monthly total costs for AFS job states in thousands, Total Cost($k) = mean monthly total costs for Tech and AFS job states, Total Production = Total airman Productive Capacity, Prod/Airman = Average Productive Capacity per airman, Cost/Position = Total Cost/StaffLevel, Cost/Prod = Total Cost/Total Production.

Prod/Airman (computed as Total Production divided by StaffSize) reflects the mean productive capacity of simulated airmen in the AFS job states. As Table 4 shows, productive capacity (Prod/Airman) was homogeneous across the four AFSs, owing in part to the nonsystematic allocation of talent in this baseline (random classification) model. Cost/Position (computed as Total Costs divided by the AFSs' StaffLevels) refers to the mean per person per month cost to maintain an approximately fully staffed specialty. Finally, Cost/Prod (computed as Total Cost divided by Total Production) can be interpreted as the cost to procure one (arbitrarily defined) unit of productive capacity.

The fifth column of Table 4 shows results for the "OtherAFS" job state. On the average, very few airmen were placed into the OtherAFS job state from BMT (vs. the four Tech job states - 1%) or from the Tech job states (vs. one of the AFS job states - 0.8%) and Costs were correspondingly small. This attests to the efficiency of the model in utilizing the majority of individuals created for the simulation. All other results are null because once individuals were transitioned into the OtherAFS job state they were defined as having no Production or Costs. Finally, the sixth column of Table 4 shows Overall results aggregated across all job states. For example, this column shows that the overall mean productive capacity for all simulated individuals was 0.652.

Table 5 shows results for Model 2, which simulated the introduction of a top-down selection strategy based on Electronics scores for AFS328x0, and random placement in the remaining AFSs. The top half of Table 5 shows mean results for the last 48 months of the simulation for Model 2. All variables are defined in the same terms as those shown in Table 4 for the baseline model. More importantly, the bottom half of Table 5 ("Relative Results") compares Model 2 results to those shown in Table 4 for the baseline model (except for AFS StaffSize, which shows mean overages or shortfalls in StaffSizes relative to desired staffing levels).

Results for AFS328x0 in Table 5 show that it experienced a slight shortfall in manpower: its mean StaffSize (1072) was 98.8% of the desired StaffLevel (1085). On the other hand, (a) Training Costs and AFS Costs were reduced, (b) Production increased (by 4.5% to 749), and (c) costs to procure productive capacity were reduced (by 4.2% to 4500), all of which were desirable outcomes. That is, overall production increased, with fewer incumbents, and at reduced costs, as a function of implementing a top-down selection strategy based on Electronics scores for AFS328x0.

But what effects did implementing this selection system have on the other AFSs and the multiple-job system as a whole? First, either Training Costs, AFS Costs, or both, increased for the three remaining specialties. Costs increased most dramatically for AFS423x5 (e.g., Total Costs increased by $2,404 per month), likely due to competition with AFS328x0 for qualified airmen, since both AFSs use E as an aptitude selector. Also, both Total Production and average production per airman (Prod/Airman, i.e., productive capacity) decreased, and cost per unit of production (i.e., Cost/Prod) increased for all three remaining AFSs. Thus, the benefits realized from implementing a top-down selection system for AFS328x0 were at least partially offset by corresponding costs (in terms of increased costs and decreased productivity) felt by the remaining AFSs. System-wide, relative results in the right-most column of Table 5 show that Overall Production per airman (mean productive capacity) remained essentially unchanged (-0.001), but that Overall Cost per productive unit decreased (-57). Thus, in comparing Model 2 to Model 1, overall efficiency (cost per productive unit) increased slightly (by 0.32%) due to large increases in efficiency in AFS328x0. However, these increases were generally offset by decreases on the other AFSs (most notably AFS423x5). These results illustrate one critical limitation to current conceptions of utility analysis: gains realized in increased productivity and decreased costs as a function of implementing a valid selection system cannot be viewed in isolation of the collateral effects that implementation of the system may have on other, organizationally interdependent jobs.

Table 5.

Model 2 Results

	AFS					
	272x0	328x0	423x5	732x0	Other	Overall
<u>Mean Results - Last 48 Months</u>						
Trng. Class Size	143	125	257	50	6	581
AFS StaffSize	1652	1072	2265	1935	57	6980
Trng. Cost($k)	1278	911	1695	649	4	4537
AFS Cost($k)	3673	2449	5131	4298	392	15942
Total Cost($k)	4951	3359	6826	4948	0	20084
Total Production	1131	749	1383	1282	0	4545
Prod/Airman	0.690	0.690	0.609	0.662	0	0.651
Cost/Position	3023	3093	3007	2554	0	2898
Cost/Prod	4371	4500	4938	3860	0	17669
<u>Relative Results</u>						
Trng. Class Size	-4	-0	3	0	-1	-1
AFS StaffSize	14	-14	-5	-2	-1	-9
Trng. Cost	-27263	-6976	22986	3972	-357	-7638
AFS Cost	2061	-3146	417	-5791	-4897	-11354
Total Cost	-25202	-10121	23404	-1819	0	-13738
Total Production	-10	32	-22	-12	0	-13
Prod/Airman	-0.006	0.029	-0.010	-0.006	0	-0.001
Cost/Position	-15	-9	10	-1	0	-2
Cost/Prod	11	-198	92	37	0	-57

<u>Note</u>. Trng. Class Size = Tech job states' StaffSizes, AFS Staffsize = AFS job states' StaffSizes, Trng. Cost($k) = mean monthly total training costs for Tech job states in thousands, AFS Cost($k) = mean monthly total costs for AFS job states in thousands, Total Cost($k) = mean monthly total costs for Tech and AFS job states, Total Production = Total airman Productive Capacity, Prod/Airman = Average Productive Capacity per airman, Cost/Position = Total Cost/StaffLevel, Cost/Prod = Total Cost/Total Production.

Table 6 shows results for Model 3, where individuals were placed into the AFS in which they had their highest standardized AFS-appropriate MAGE score. Focusing on the Relative Results, Table 6 shows that there were only slight differences between Model 3's and Model 1's Training Class Sizes, and between Model 3's AFS StaffSizes and the desired staffing levels, with AFS272x0 being slightly overpopulated on the average (100.5% of StaffLevel) and AFS423x5 slightly underpopulated (99.4% of StaffLevel). Total Costs were reduced in three of the four AFSs (with a maximum reduction of 0.34% for AFS423x5), but increased in AFS328x0 (by 0.12%). Similarly, Production increased in three out of the four AFSs (by as much as 9.5% in AFS423x5), and decreased by 5.7% in AFS328x0. Finally, Cost per Productive Unit decreased by as much as 8.9% for AFS423x5 and increased by as much as 6.1% for AFS328x0. Comparing system-wide (Overall) Relative Results to Model 1, Model 3 resulted in a 2.6% increase in Total Production (i.e., from 4558 to 4676), a 2.8% increase in average Prodction/Airman (productive capacity, from 0.652 to 0.670), and a 1.4% reduction in Cost per Productive Unit (from $17,726 to $17,485.

Table 7 shows results for Model 4, which optimized placement of individuals based on standardized AFS-appropriate MAGE scores. Once again, Training Class Sizes were very close to those in the baseline model, and AFS StaffSizes were very close to their desired StaffLevels, with AFS272x0 being slightly overstaffed (100.5% of StaffLevel) and AFS423x5 slightly understaffed (99.3% of StaffLevel). Here however, Total Costs decreased in two AFSs (by as much as 0.19% for AFS423x5) and increased in the other two (by as much as 0.14% for AFS732x0) as compared to the baseline model. Overall, however, Total Costs remained essentially flat (overall reduction of 0.008%). On the other hand, Total Production increased by 2.8%, Production per Airman increased by 2.9%, and Cost per Unit of Production decreased by 2.4% compared to the baseline model (Model 1).

One interesting question concerns the relative efficiency of the Placement model (Model 3) versus the Optimized Placement model (Model 4). One general trend was for Model 3 to emphasize increased payoffs (e.g., reduced costs, increased production) for AFS423x5 at the expense of AFS328x0. On the other hand, costs and benefits were more evenly distributed in Model 4. However, by comparing results in the top halves of Tables 6 and 7, it can be shown that Model 4 (Optimized Placement) realized quite small increases in Total Production (0.17%, i.e., 4676 for Model 3 vs. 4684 for Model 4) and Production per Airman (0.15%), and a small decrease in Cost per Productive Unit (0.04%) relative to Model 3 (Placement). Thus, gains of the optimized placement model over the placement model were small.

Table 8 shows results for Model 5 which, like Model 3, placed airmen from BMT into the four AFSs. However, placement in Model 5 was on the basis of predicted performance, or performance predicted on the basis of MAGE composites and AFQT scores. As in Model 3, Model 5 reduced Total Costs in three of the AFSs compared to Model 1 (by as much as 0.22% for AFS423x5) and increased costs in AFS328x0 (by 1.6%). However, unlike Model 3, Total Production and Production per Airman increased, and Cost per Productive Unit decreased for all AFSs. Overall, compared to the baseline model, Total Production and Production per Airman increased by 5.0% and 5.2% respectively, and Cost per Productive Unit decreased by 5.2%.

Table 6.

Model 3 Results

	AFS					
	272x0	328x0	423x5	732x0	Other	Overall
Mean Results - Last 48 Months						
Trng. Class Size	146	125	250	49	6	576
AFS StaffSize	1647	1084	2257	1939	57	6984
Trng. Cost($k)	1300	921	1650	637	3	4512
AFS Cost($k)	3670	2452	5130	4303	387	15943
Total Cost($k)	4970	3374	6780	4940	0	20064
Total Production	1147	677	1538	1314	0	4676
Prod/Airman	0.700	0.624	0.677	0.678	0	0.670
Cost/Position	3034	3107	2987	2551	0	2895
Cost/Prod	4327	4984	4415	3760	0	17485
Relative Results						
Trng. Class Size	-1	0	-3	-1	-1	-5
AFS StaffSize	9	-2	-13	2	-1	-5
Trng. Cost	-5412	3509	-22221	-8512	-490	-33125
AFS Cost	-641	634	-566	-445	-9645	-10664
Total Cost	-6053	4142	-22787	-8957	0	-33654
Total Production	7	-40	133	19	0	118
Prod/Airman	0.004	-0.037	0.059	0.010	0	0.017
Cost/Position	-4	4	-10	-5	0	-5
Cost/Prod	-33	286	-431	-64	0	-241

Notes. Trng. Class Size = Tech job states' StaffSizes, AFS Staffsize = AFS job states' StaffSizes, Trng. Cost($k) = mean monthly total training costs for Tech job states in thousands, AFS Cost($k) = mean monthly total costs for AFS job states in thousands, Total Cost($k) = mean monthly total costs for Tech and AFS job states, Total Production = Total airman Productive Capacity, Prod/Airman = Average Productive Capacity per airman, Cost/Position = Total Cost/StaffLevel, Cost/Prod = Total Cost/Total Production. Relative cost results are presented in dollars.

Table 7.

Model 4 Results

	AFS					
	272x0	328x0	423x5	732x0	Other	Overall
Mean Results - Last 48 Months						
Trng. Class Size	145	125	252	50	6	578
AFS StaffSize	1646	1086	2253	1937	55	6976
Trng. Cost($k)	1295	915	1661	655	4	4530
AFS Cost($k)	3671	2454	5129	4302	374	15930
Total Cost($k)	4967	3370	6790	4956	0	20082
Total Production	1160	674	1542	1308	0	4684
Prod/Airman	0.708	0.621	0.679	0.676	0	0.671
Cost/Position	3032	3103	2991	2559	0	2897
Cost/Prod	4279	5001	4411	3788	0	17478
Relative Results						
Trng. Class Size	-2	-0	-2	1	-0	-3
AFS StaffSize	8	-0	-17	-0	-3	-13
Trng. Cost	-10146	-2524	-11144	9363	-93	-14544
AFS Cost	286	2552	-1583	-2359	-22704	-23807
Total Cost	-9860	28	-12728	7004	0	-15555
Total Production	19	-44	137	14	0	126
Prod/Airman	0.012	-0.040	0.060	0.007	0	0.019
Cost/Position	-6	0	-6	4	0	-2
Cost/Prod	-81	304	-435	-36	0	-248

Notes. Trng. Class Size = Tech job states' StaffSizes, AFS Staffsize = AFS job states' StaffSizes, Trng. Cost($k) = mean monthly total training costs for Tech job states in thousands, AFS Cost($k) = mean monthly total costs for AFS job states in thousands, Total Cost($k) = mean monthly total costs for Tech and AFS job states, Total Production = Total airman Productive Capacity, Prod/Airman = Average Productive Capacity per airman, Cost/Position = Total Cost/StaffLevel, Cost/Prod = Total Cost/Total Production. Relative cost results are presented in dollars.

Table 8.

Model 5 Results

	AFS					
	272x0	328x0	423x5	732x0	Other	Overall
<u>Mean Results - Last 48 Months</u>						
Trng. Class Size	143	131	251	50	6	581
AFS Staffsize	1635	1093	2263	1938	56	6984
Trng. Cost($k)	1270	970	1658	647	4	4548
AFS Cost($k)	3670	2455	5130	4302	379	15936
Total Cost($k)	4940	3425	6788	4949	0	20101
Total Production	1153	782	1501	1352	0	4788
Prod/Airman	0.704	0.720	0.661	0.698	0	0.686
Cost/Position	3016	3154	2990	2555	0	2900
Cost/Prod	4287	4369	4527	3662	0	16844
<u>Relative Results</u>						
Trng. Class Size	-4	6	-2	0	-1	-1
AFS Staffsize	-3	7	-7	1	-3	-5
Trng. Cost	-35195	52184	-14308	1135	-331	3484
AFS Cost	-1302	3015	-548	-1701	-17362	-17898
Total Cost	-36497	55199	-14856	-566	0	3279
Total Production	13	65	96	57	0	230
Prod/Airman	0.008	0.060	0.042	0.029	0	0.033
Cost/Position	-22	51	-7	-0	0	0
Cost/Prod	-72	-329	-319	-162	0	-883

<u>Notes</u>. Trng. Class Size = Tech job states' StaffSizes, AFS Staffsize = AFS job states' StaffSizes, Trng. Cost($k) = mean monthly total training costs for Tech job states in thousands, AFS Cost($k) = mean monthly total costs for AFS job states in thousands, Total Cost($k) = mean monthly total costs for Tech and AFS job states, Total Production = Total airman Productive Capacity, Prod/Airman = Average Productive Capacity per airman, Cost/Position = Total Cost/StaffLevel, Cost/Prod = Total Cost/Total Production. Relative cost results are presented in dollars.

Finally, Table 9 shows results for Model 6, in which classification occurred as a function of optimized placement on the basis of predicted performance from MAGE composites and AFQT scores. Here, Total Costs actually increased for three AFSs as compared to Model 1 (by as much as 1.2% for AFS328x0), but decreased for AFS272x0 (by 2.1%), and overall (-.06%). However, Total Production and Production per Airman increased, and Cost per Productive Unit decreased uniformly across all AFSs. Overall relative to the baseline model, Total Production and Production per Airman increased by 4.9% and 5.1% respectively, and Cost per Productive Unit decreased by 5.2%. Surprisingly, these results for the optimized placement model were negligibly different compared to Model 5 (placement model).

One final comparison that we undertook was one between placement based on AFS-appropriate MAGE scores (Models 3 and 4) versus placement based on predicted performance from MAGE composites and AFQT scores (Models 5 and 6). For this we chose to compare Overall results for optimized placement models (Model 4 vs. Model 6). Compared to Model 4, Model 6 resulted in a 2.1% increase in both Total Production and Production per Airman, and a 3.8% reduction in Cost per Productive Unit. This suggests that additional classification efficiency could be achieved by optimizing classification decisions on the basis of standardized performance scores predicted on the basis of all four MAGE composites and AFQT scores, as compared to classification based solely on AFS-appropriate MAGE selector composites.

IV. DISCUSSION

The purposes of the work reported here were to (a) demonstrate the viability of computer simulation modeling as an alternative to more traditional approaches to examining the utility of human resource management interventions, (b) examine tradeoffs between single-job utility, broadly defined, and overall system utility in an interdependent multiple-job system, and (c) evaluate the relative utility of alternative personnel classification policies. We achieved the first goal in Phase I of this work by replicating analytically-derived results presented earlier by Carpenter et al. (1989) on the TTP model using MPlanSim, a general computer simulation modeling program developed by Ladd and Kudisch (1994). We achieved the second and third goals in Phase II by using MPlanSim to model a dynamic, interdependent system of four AFSs that had been studied previously as part of the JPM Project.

Results indicated that (a) more favorable outcomes could be achieved for AFSs singly, but at the expense of outcomes for other AFSs (i.e., Model 2), (b) placing individuals in the AFS for which they were most qualified (Model 3) resulted in significant system-wide improvement over using only minimal cut scores (Model 1) even when the criteria were the same (i.e., MAGE selector composites), (c) optimizing outcomes across the entire multiple-job system involved tradeoffs in outcomes between the AFSs studied, (d) even when there were small system-wide differences in outcomes, significant within-job differences in outcomes resulted for optimized placement versus simple placement, and (e) optimized placement based on predicted performance, rather than on MAGE qualifying scores, resulted in more efficient classification decisions.

Table 9.

Model 6 Results

	AFS					
	272x0	328x0	423x5	732x0	Other	Overall
<u>Mean Results - last 48 Months</u>						
Trng. Class Size	141	129	254	50	6	580
AFS Staffsize	1639	1094	2260	1937	56	6986
Trng. Cost($k)	1249	957	1673	655	3	4538
AFS Cost($k)	3674	2455	5133	4299	383	15944
Total Cost($k)	4923	3412	6806	4954	0	20095
Total Production	1168	777	1499	1338	0	4783
Prod/Airman	0.713	0.716	0.660	0.691	0	0.685
Cost/Position	3006	3142	2998	2558	0	2899
Cost/Prod	4214	4380	4545	3703	0	16843
<u>Relative Results</u>						
Trng. Class Size	-6	4	0	1	-1	-2
AFS Staffsize	1	8	-10	0	-2	-3
Trng. Cost	-56330	38847	828	9930	-530	-7255
AFS Cost	3322	3250	2447	-5359	-13652	-9992
Total Cost	-53008	42097	3274	4571	0	-3066
Total Production	28	60	94	43	0	225
Prod/Airman	0.017	0.055	0.041	0.022	0	0.032
Cost/Position	-32	39	1	2	0	-0
Cost/Prod	-145	-317	-301	-121	0	-884

<u>Notes</u>. Trng. Class Size = Tech job states' StaffSizes, AFS Staffsize = AFS job states' StaffSizes, Trng. Cost($k) = mean monthly total training costs for Tech job states in thousands, AFS Cost($k) = mean monthly total costs for AFS job states in thousands, Total Cost($k) = mean monthly total costs for Tech and AFS job states, Total Production = Total airman Productive Capacity, Prod/Airman = Average Productive Capacity per airman, Cost/Position = Total Cost/StaffLevel, Cost/Prod = Total Cost/Total Production. Relative cost results are presented in dollars.

Implications

First, results presented here support the idea that CSM is a viable alternative to more traditional approaches to the assessment of outcomes of human resource management (HRM) interventions. Although traditional utility models and their more recent embellishments (Boudreau, 1991) have proven valuable in (a) focusing human resource scientists and practitioners on the value of HRM interventions, and (b) providing analytic models to quantify HRM intervention costs and benefits, their limitations are becoming more widely recognized. We see CSM as a much broader and flexible approach for evaluating HRM intervention outcomes, and one that holds more traditional utility models as special cases.

A second implication concerns one of the key limitations to traditional utility models that we addressed here, namely the interdependencies that often exist among jobs in organizations. Results for Model 2 confirmed many findings reported earlier in the utility analysis literature: implementation of a valid selection system results in reduced costs and increased productivity in the target job. However, what has not been reported in this literature is the impact that implementing a valid selection system in one job has on other interdependent jobs. Results for Model 2 showed that implementing a top-down valid selection system in one job does result in cost reductions and productivity enhancement in the target job (AFS328x0 here), but at the expense of these outcomes in other jobs. This is an issue that has been almost completely neglected in the personnel utility literature, but one which needs further attention. The simulations reported here addressed interdependencies among different jobs within a single organization, or job-level competition for available talent. Other issues that need to be addressed include competition among similar jobs in different organizations for available talent in the labor market and, perhaps competing career options for those in the labor market. Extending research to address real-world complexities such as these can quickly render traditional analytic approaches to utility analysis intractable, but are more easily addressed using CSM.

Third, we examined placement versus classification (optimized placement) as alternative personnel classification strategies in a prototype interdependent multiple-job system. These are conceptually distinct personnel assignment policies. Whereas placement is designed to optimize individual assignments to job openings, optimized placement (classification) seeks to optimize a payoff function associated with the system as a whole. Practically speaking, the results reported here found little difference between these two assignment strategies in terms of overall system payoffs. Given its additional computational complexity, and the operational problem of assigning individuals to jobs other than the one for which they are most qualified, the utility of the more complicated classfication strategy over the simpler placement strategy must be questioned. However, one thing that must be borne in mind is that increases in the efficiency of either of these differential assignment strategies will be greater to the extent that the abilities and the jobs' ability requirements are truly differentiated, that is, that different jobs require different abilities that themselves are not highly correlated. This was clearly not the case here. AFS-appropriate MAGE composites were highly correlated, thus reducing the potential for differential personnel assignment strategies to show gains over a much simpler strategy which involves top-down selection followed by random assignment (i.e., Model 1). Thus, although placement and classification strategies both realized gains in overall personnel assignment efficiency

over the random selection model, much greater gains would be expected if relevant aptitudes and the job's aptitude requirements were more distinct.

Finally, results showed better classification efficiency when personnel were assigned on the basis of predicted performance as opposed to using AFS-appropriate MAGE cutoff scores. This is easily explained. Assignment based on predicted performance takes more information into account in forecasting an individual's likelihood of success in a particular job (i.e., all MAGE scores) than does assignment based on only one aptitude index. This raises the practical issue of possibly basing assignment decisions on predicted performance rather than on meeting specified aptitude cutoff scores. However, there is the other operational issue of negative regression weights being applied to some of the individual aptitude predictors, creating the potential for persons being denied an opportunity for a position because they scored particularly well on one or more of the ASVAB subtests. Nevertheless, results for Models 3 through 6 permit some assessment of the implications of tradeoffs between assignment efficiency and operational realities.

Limitations and Directions for Future Research

An obvious limitation to the present work is the limited job system studied here. Although the work we reported represents a substantial extension to existing research on evaluating outcomes of HRM interventions, if falls short of representing the entire system within which it is embedded. We simulated employee accession, classification, training, and transition through the first term of enlistment for four interdependent AFSs. However, there are over 300 AFSs in the USAF enlisted occupational structure (AFR 39-1). Thus, even though our simulation models of job states, variables, employee flows, and staff levels were complex, they failed to capture the actual complexity of the fuller system. Nevertheless, the principles governing our representation of this simple subsystem should generalize to the description of the entire system. The extent to which our results would generalize to this larger system is unknown. Thus, one obvious direction for research, and perhaps as an aid for shaping selection and classification policy, would be to begin to enlarge the subsystem of AFSs examined in future simulation work.

A second limitation of our work is that we examined only the more typical employee flows across the first term of enlistment. This was mentioned earlier in the context of delimiting the multiple-job system that we would model. Some USAF enlistment, classification, and training policies, for example, the Guaranteed Enlistment Program, consideration of airman occupational preferences in classification, cross-job retraining, and early outs, simply were not represented in our simulation models. However, these could also be incorporated in future, more elaborate simulation modeling.

Third, obviously there are additional determinants of the outcomes we studied that were not included in our simulation models. A brief list of these factors includes motivational determinants of productivity, geographical or career-related preferences in classification decisions, and shifts in manpower needs associated with emerging conflict. Once again, however, additional factors such as these also could be incorporated into future simulation models.

Fourth, our focus was restricted to the first term of enlistment. In part, this was dictated by our intention to replicate Carpenter et al'.s (1989) earlier results, and in part, it was arbitrary in the multiple-job simulations. Extensions of the work that we presented to include transition into "career airmen" job states would represent another relatively straightforward extension to the present work.

Finally, we used historical data to estimate simulation model parameters (e.g., selection ratios, training attrition rates) when in fact economic, geopolitical, and demographic changes that are now occurring in the United States and worldwide may well affect these estimates. This limitation of the present work actually points to one of the main strengths of CSM, namely, the capacity to anticipate changes such as these and to simulate their possible effects before they actually occur.

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APPENDIX A

DETAILED DESCRIPTION OF MULTIPLE-JOB SIMULATION VARIABLES

DETAILED DESCRIPTION OF MULTIPLE-JOB SIMULATION VARIABLES

One key component of the multiple-job system simulation model was a specification of the characteristics of individuals ("Person Variables"), job states ("Job Variables"), and the model as a whole ("Global Variables") that would be simulated, how these would be modeled, and how they would be tracked over the course of the simulation. Appendix A provides a detailed description of the specification of each of these classes of variables as they were implemented in the multiple-job system simulations. This section describes these decisions as they concern individual-level (person) variables.

Person Variables

In order to track individual-level data through the simulation, each individual was assigned a cardinal identification number (ID). Other individual-level variables related to aptitude, experience (tenure), and productivity. The following sections describe how these variables were created (initialized) and recalculated over the course of the simulations.

Aptitude. Individuals were assigned values simulating Mechanical, Administrative, General, and Electronics (MAGE) composite scores, as well as an AFQT composite score. This was accomplished as follows. First, the correlations among the AFQT and MAGE composites were obtained from Maier and Sims (1986). These are reproduced in Table A1. Second, the five components of this matrix were computed. AFQT and MAGE composites' loadings on these components are shown in Table A2.

Table A1

Correlations Among AFQT and MAGE Composites

	1	2	3	4	5
1. AFQT	1.0000				
2. Mechanical	.7059	1.0000			
3. Administrative	.8629	.5546	1.0000		
4. General	.9784	.7351	.8403	1.0000	
5. Electronics	.9053	.8319	.7469	.9290	1.0000

Note. Correlations reported in Maier and Sims (1986).

Third, five independent standard normal deviate scores (pc1 through pc5) were created in MPlanSim by drawing random numbers from a standard normal distribution (see Figure A1). These

were assigned to each individual which was "created" for the simulation. Fourth, standardized AFQT and MAGE scores (zAFQT, zM, zA, zG, and zE) were computed from the component weights shown in Table A2. Thus these standard scores preserved the correlational structure among the aptitude

composites as shown in Table A1. Finally, these z-scores were converted to their percentile equivalents to create new variables (AFQT, M, A, G, and E) using a function "Centile" which is shown in Figure A2. The function "Centile" graphically equates AFQT and MAGE z-scores into their percentile-metric equivalents. These aptitude scores were used (a) to simulate USAF entrance requirements, (b) as part of the personnel classification simulation, and (c) as determinants of individual productivity.

Table A2

Loadings of AFQT and MAGE Composites on the Five Components Computed From Correlations in Table A1

	Components				
	I	II	III	IV	V
AFQT	-.9704	-.1467	.1251	-.1139	-.0909
Mechanical	-.8248	.5288	-.1905	-.0618	.0006
Administrative	-.8704	-.4033	-.2782	.0482	.0057
General	-.9768	-.0872	.1516	-.0712	.1015
Electronics	-.9594	.1485	.1354	.1970	-.0171

Tenure. Six tenure-related variables were created. One ("TAFMS") indexed individuals' total service time in the simulation and thus reflected first-term enlistees' Total Active Federal Military Service. As is shown in Figure A1, this variable was initialized at 0, indicating that at the time an individual is created for the simulation they have zero months of tenure in the USAF. As is shown in Figure A3, values of TAFMS were recalculated each time period (month) by incrementing the current value of TAFMS by 1 to indicate the accrual of one additional month of tenure. TAFMS was used to (a) transition individuals across job states at appropriate times in the simulation, (b) as one determinant of productivity (a surrogate for experience), (c) to determine appropriate times at which pay raises would be given, and (d) to exit individuals from the simulation at the end of 48 months.

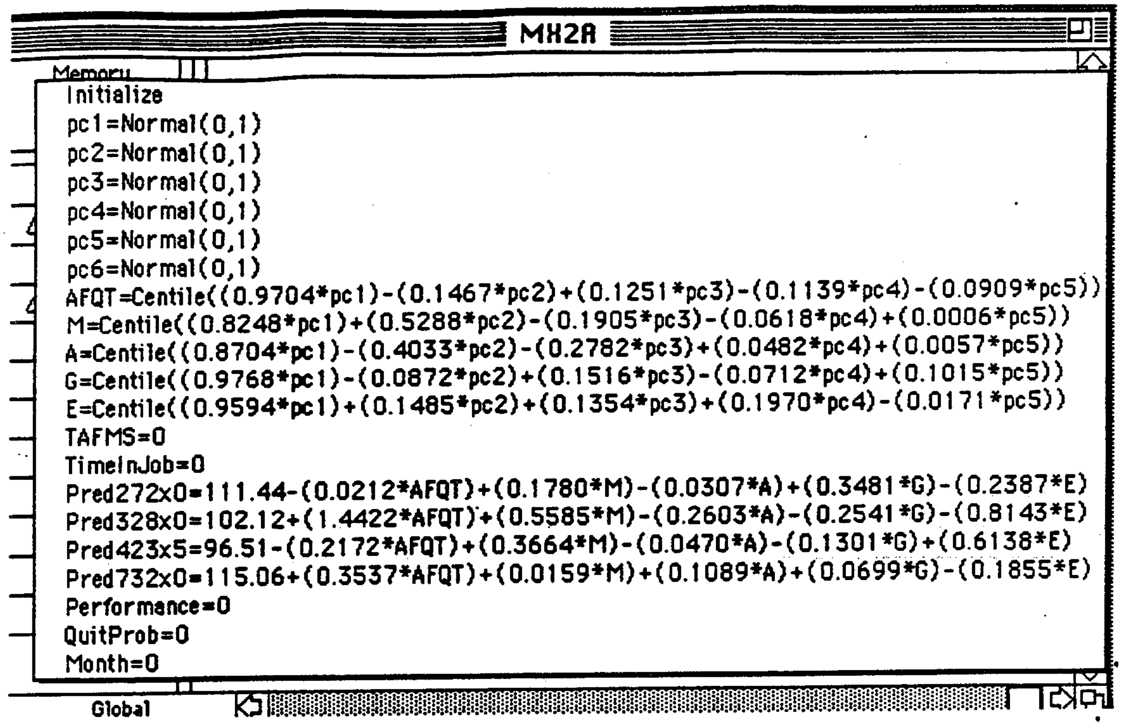

Figure A1: Variables' Initialization Formulae

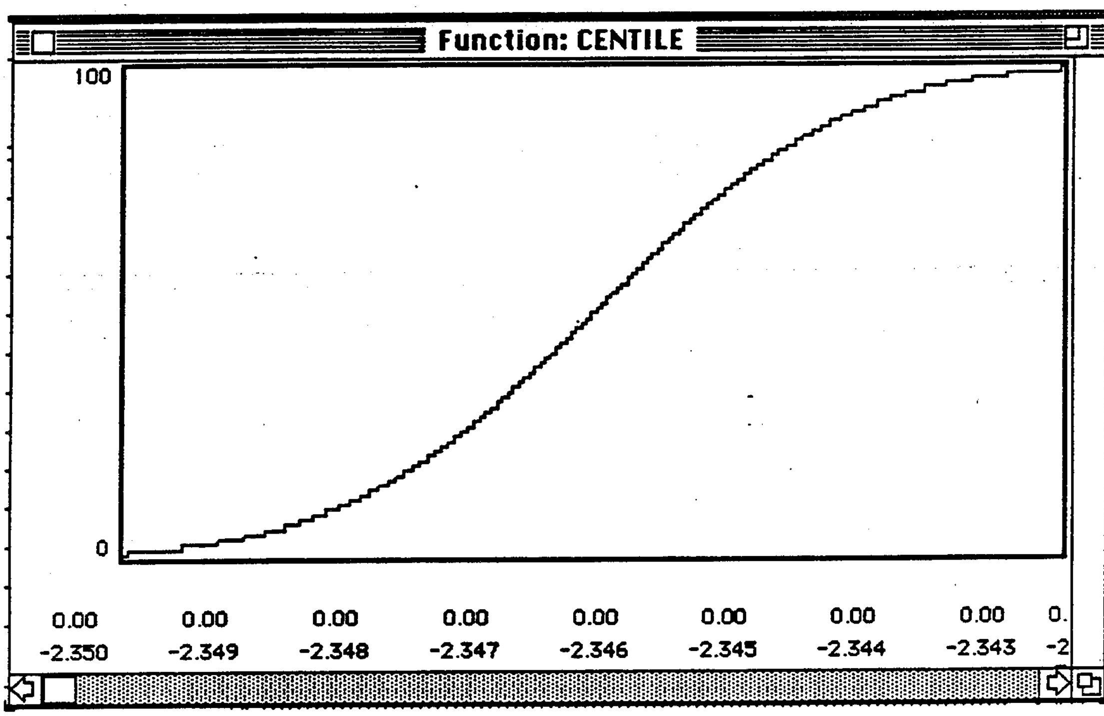

Figure A2: "Centile" Function

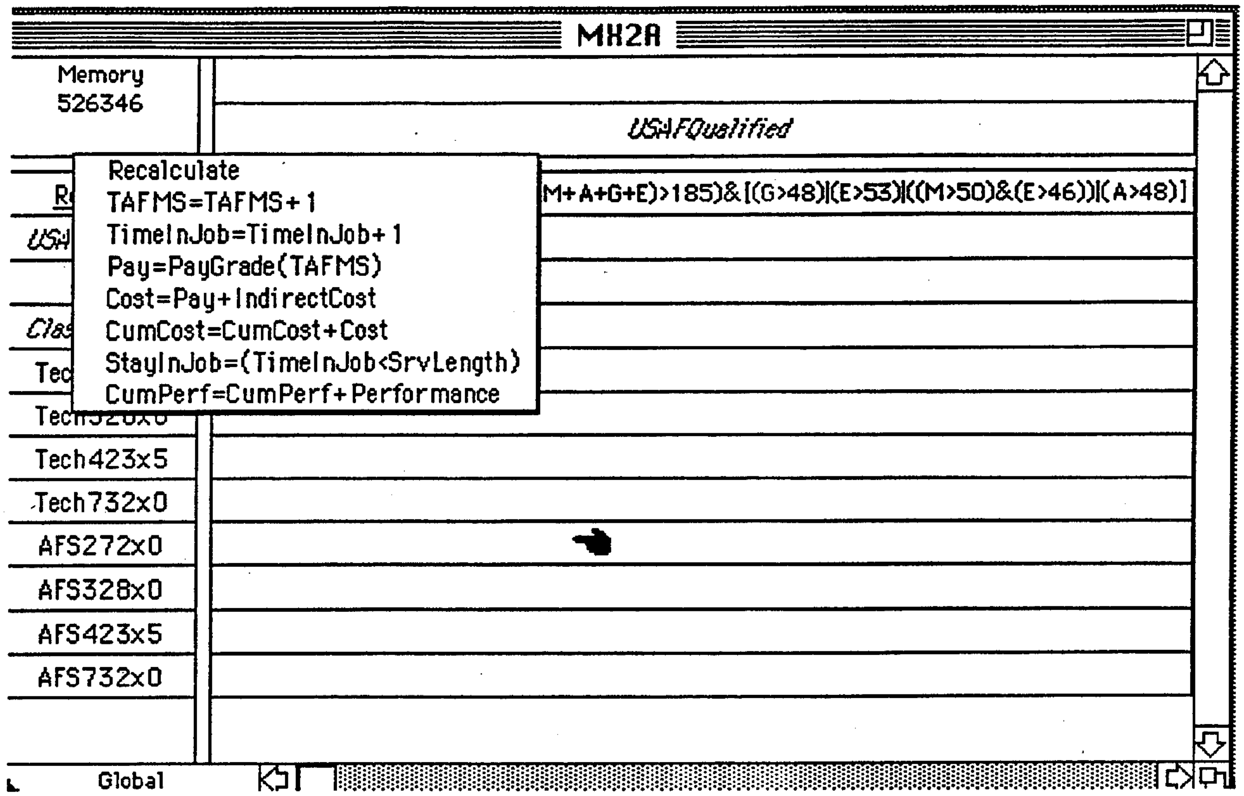

Figure A3: Global Recalculation Formulae

A second tenure-related variable ("TimeInJob") was defined to track individuals' tenure in particular job states. As with TAFMS, TimeInJob was initialized at 0 at the beginning of the simulation. However, TimeInJob was re-initialized equal to 1 every time an individual was transitioned from one job state into another so that after the time period during which the individual was transitioned they had one month of tenure in the new job state. As with TAFMS, TimeInJob was recalculated monthly by incrementing its value by 1 to indicate an additional month of accrued experience in the particular job state (see Figure 16).

A third tenure-related variable "QuitProb," determined the probability of any simulated individual exiting the system in a given month of the simulation. QuitProb was determined separately for each job state and is described in more detail in Appendix C. Two other variables "StayInJob" and "NewJob," were binary variables which, conditional on length of service, indicated whether each simulated individual was to remain in the current job state for the upcoming month (StayInJob = 1), or whether the individual was targeted to transition into some other job state (NewJob = 1). As is discussed in Appendix B, these variables were used to forecast manpower needs in the AFS and Tech

job states. Finally, BMTMth was a binary variable which was equal to 1 for each simulated individual targeted to exit the system and was used to forecast replacement needs for recruitment into BMT.

Productivity. Six variables relating to individual productivity were defined. The first four ("Pred272x0" through "Pred732x0") were indexes of predicted performance levels in each of the four AFSs. These were used in personnel placement and optimization algorithms. Initialization formulae for Pred272x0 through Pred732x0 (shown in Figure A1) were estimated from the JPM data bases for AFSs 272x0, 328x0, 423x5 and 732x0. Specifically, formulae shown in Figure A1 are ordinary least squares results from the regression of Walk-Through Performance Test (WTPT) total scores on AFQT and MAGE percentile scores. Samples' descriptive statistics on these variables are shown in Table A3. Unstandardized regression results are shown in Table A4.

The fifth productivity-related variable ("Performance") was defined to index simulated individuals' performance during the simulation. Performance was conceptually similar to Carpenter et al.'s (1989) "Productive Capacity," in several ways. First, as in the TTP model, it was assumed that performance was zero until simulated airmen reached one of the AFS job states. Therefore, each simulated airman's Performance was initialized at zero and remained equal to zero through the duration of BMT and RTT. Second, as in the TTP model, it was assumed that aptitude and accrued experience were the major determinants of Performance. Third, Performance was referenced to maximum possible performance as in the TTP model. However, unlike the TTP model, a random error component was added to Performance to more realistically represent the stochastic portion of job performance.

Specifically, each simulated airman's Performance was initialized equal to zero upon transition into one of the AFS job states. Thereafter, Performance was recalculated monthly (a) using results from regressing WTPT total scores on TAFMS, and AFQT and MAGE percentile scores (shown in Table A5), (b) adding a random error component to Performance, and (c) referencing each simulated airman's performance to maximum attainable Performance. For example, Performance in AFS272x0 was recalculated monthly as:

$$\begin{aligned}\text{Performance} = [&98.12 + .0959*\text{AFQT} + .0929*\text{M} - .0100*\text{A} + \\ &.3794*\text{G} - .1211*\text{E} + .4688*\text{TAFMS} + 18.03*\text{pc6}]/207, \end{aligned} \tag{A1}$$

where coefficients for TAFMS and the AFQT and MAGE composites are from Table A5, the coefficient for pc6 (a standard normal deviate) was chosen so as to reproduce the $\underline{R}^2$ for AFS272x0 in Table A5, and the divisor 207 equals 1 plus the maximum performance observed for Equation A1 among 10,000 individuals in pilot simulation runs. This, and the remaining Performance recalculation equations are shown in Table A6.

Table A3

JPM Data Sample Descriptive Statistics

	AFS272x0	AFS328x0	AFS423x5	AFS732x0
WTPT Total Score:				
Mean	129.19	157.24	140.92	138.33
sd	19.33	22.91	23.31	20.87
AFQT Percentile:				
Mean	72.79	80.70	58.64	58.34
sd	15.04	12.37	16.44	17.41
Mechanical:				
Mean	72.08	85.14	76.04	46.06
sd	20.00	11.39	13.16	22.02
Administrative:				
Mean	69.30	71.07	53.99	73.15
sd	18.38	18.55	18.81	14.57
General:				
Mean	74.74	80.83	59.76	57.80
sd	14.71	13.75	16.73	17.56
Electronics:				
Mean	73.01	85.69	64.52	54.45
sd	15.14	9.13	15.67	18.05
TAFMS:				
Mean	26.89	35.28	28.11	27.87
sd	8.84	14.54	10.42	11.78

Note. JPM = Job Performance Measurement, WTPT = Walk-Through Performance Test Score, AFQT = Air Force Qualifications Test Composite, TAFMS = Total Active Federal Military Service.

Table A4

Unstandardized Regression Results From the Prediction of WTPT From AFQT and MAGE Composite Percentile Scores

AFS	N	R^2	Int.	AFQT	M	A	G	E
272x0	172	.05	111.88	-.021	.178	-.031	.348	-.239
328x0	83	.25**	102.12	1.442*	.559*	-.260	-.254	-.814
423x5	219	.14**	96.50	-.217	.366**	-.047	-.130	.613**
732x0	179	.08*	115.06	.354	.016	.109	.070	-.185

Note. N = sample size, R^2 = squared multiple correlation, WTPT = Walk-Through Performance Test Score, AFQT = Air Force Qualification Test Percentile Score; M = Mechanical A = Administrative, G = General, and E = Electronics composite percentile scores.

*p<.05; **p<.01.

Table A5

Unstandardized Regression Results From the Prediction of WTPT from TAFMS and AFQT and MAGE Composite Percentile Scores

AFS	R^2	Int.	AFQT	M	A	G	E	TAFMS
272x0	.09*	98.12	-.096	.092	-.010	.379	-.121	.469**
328x0	.34**	95.86	1.567*	.423	-.228	-.301	-.902*	.472**
423x5	.21**	82.50	-.119	.390**	-.026	-.178	.489*	.578**
732x0	.20**	97.06	.221	.050	.135	.133	-.073	.612**

Note. R^2 = squared multiple correlation, WTPT = Walk-Through Performance Test Score, AFQT = Air Force Qualification Test Percentile Score; M = Mechanical A = Administrative, G = General, and E = Electronics composite percentile scores, TAFMS = Total Active Federal Military Service.

*p<.05; **p<.01.

Table A6

Recalculation Formulae for Performance

AFS272x0	[98.12 + .0959*AFQT + .0929*M - .0100*A + .3794*G - .1211*E + .4688*TAFMS + 18.03*pc6]/207
AFS328x0	[95.86 + 1.5671*AFQT + .4235*M - .2276*A - .3009*G - .9019*E + .4718*TAFMS + 12.88*pc6]/229
AFS423x5	[82.50 - .1193*AFQT + .3900*M - .0261*A - .1781*G + .4891*E + .5785*TAFMS + 15.93*pc6]/222
AFS732x0	[97.06 + .2213*AFQT + .0496*M + .1348*A - .1332*G - .0729*E + .6117*TAFMS + 17.75*pc6]/221

The final productivity-related variable ("CumPerf") was defined to cumulate individual Performance across time periods as long as individuals remained in the simulation (i.e., up to as long as 48 Months). Thus, CumPerf was initialized at zero and was recalculated monthly to increment its value by the current month's Performance level (see Figure 16). Conceptually, CumPerf reflects an individual's total productivity contributions throughout the duration of their tenure as an incumbent.

Costs. Four cost variables were defined from information presented in the Air Training Command Cost Factors Manual (1992). The first ("Pay") was designed to reflect monthly salary and benefits plus adjustments across the first term (standard composite rate without PCS). It was assumed that each airman would remain an E-1 for months 1-6 (monthly pay $1,423), an E-2 for months 7-16 ($1,716 per month), an E-3 for months 17-36 ($1,938 per month) and E-4 for months 37-48 ($2,322 per month) of the simulation. These values were recalculated monthly from a function "Paygrade" (see Figure A4) which modeled Pay as a function of TAFMS (i.e., Pay = Paygrade(TAFMS)).

The second cost-related variable "IndirectCost," was defined to reflect training and indirect costs. Yearly indirect costs were estimated at $3,363, or $280 per month (ATC Cost Factors, 1992). Table A7 shows the calculation of training costs. RTT durations and total costs were obtained from

ATC Cost Factors (1992). Total training costs were divided by the simulated duration of each training state to calculate a monthly training cost. Thus for each training job state, IndirectCost was initialized at the monthly training cost plus indirect costs (e.g., for AFS272x0, $4,874 + $280 = $5,154) and remained a constant for the airman's duration within the training job state. IndirectCost for the AFS job states was a constant $280 per month.

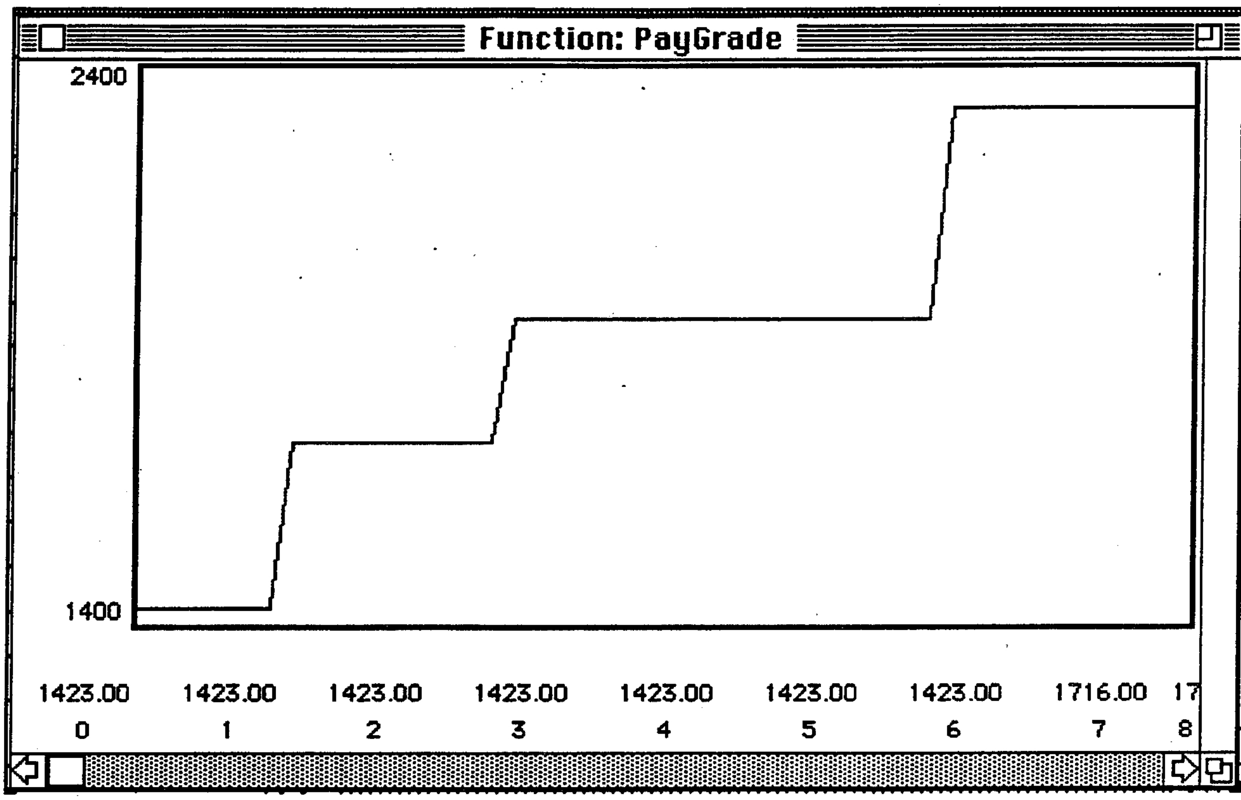

Figure A4: "Paygrade" Function

Table A7

Training Costs

Job State	Duration in weeks[1]	Simulated Duration	Training Cost Total[1]	Simulated Monthly Cost
BMT	6.0	2 mos.	$ 3,420	$ 1,710
Tech272x0	15.0	3 mos.	$14,622	$4,784
Tech328x0	17.5	4 mos.	$15,547	$3,887
Tech423x5	16.2	4 mos.	$12,722	$3,181
Tech732x0	5.8	1 mo.	$ 4,522	$4,522

[1]From ATC Cost Factors (1992)

The third cost-related variable was Cost, which was calculated monthly as Pay plus IndirectCost. Thus Costs increased from BMT to RTT with increased training costs, and then decreased after graduation from training, indicating that only Pay and indirect costs were contributing to overall Costs. The final cost-related variable, "CumCost" was initialized at zero and was recalculated monthly as CumCost = CumCost + Cost. Thus CumCost was defined to track the cumulative Costs incurred over the course of a simulated airman's first term.

Job Variables

Seven job-level variables were defined. First, "JobID," was cardinal number that enabled the tracking individuals' locations in the simulation. Second, "StaffLevel" indicated the desired staffing levels (numbers of simulated airmen) in each of the job states. The calculation of StaffLevels for each of the job states is discussed in greater detail in Appendix B. The third variable "StaffSize" tracks the actual numbers of individuals in each job state. As is also discussed in Appendix B, differences between StaffLevels and StaffSizes were used in the recalculation of various job states' Stafflevels to correct for personnel imbalances during the course of the simulation.

A fourth variable "SrvLength," refers to the duration of each job state, or the length of time individuals are held in each job state. SrvLengths for each of the training job states are shown in Table A7 under the "Simulated Duration" column. SrvLengths for the AFS job states were calculated as 48 months (i.e., length of a first term enlistment) minus RTT length, minus BMT SrvLength (e.g., for AFS272x0 SrvLength = 48 - 2 - 3 = 43 mos.).

A fifth job-level variable "IndirectCost," was discussed earlier in the determination of individual-level cost factors. Finally, "MthsNeed" and "BMTNeed" were job-level variables that were used to forecast manpower needs in the RTT and BMT training states, respectively. These are also discussed in greater detail in Appendix B.

Global Variables

One global variable was defined: "Month" was defined to track the simulation time periods (i.e., months).

APPENDIX B

DETAILED DESCRIPTION OF MULTIPLE-JOB SIMULATION STAFFING LEVELS

DETAILED DESCRIPTION OF MULTIPLE-JOB SIMULATION STAFFING LEVELS

StaffLevels, or the desired number of individuals in each of the job states shown in Figures 12 and 13, were determined from PACE Master file historical data on length of Technical Training, and from Uniform Airman Record (UAR) data on numbers of actual USAF incumbents populating the AFSs studied over the period 1980-1991. First, and as discussed in Appendix A, we determined RTT length for each of the four AFSs from ATC Cost Factors (1992). Second, it was assumed that the duration of BMT was 2 months for all new recruits (6 weeks plus transition time). Thus the number of months of Incumbency was calculated as 48 months minus 2 months BMT minus RTT duration. StaffLevels were determined from the most recently available UAR data (SEP 91) as the total number of 3- and 5-skill level airmen actually in each of the four AFSs studied. These StaffLevels are shown in Table B1.

Table B1
Incumbency Job States' StaffLevels

AFS	StaffLevel
AFS 272x0	1638
AFS 328x0	1086
AFS 423x5	2270
AFS 732x0	1937

StaffLevels for BMT and for the Tech job states were implemented in MPlanSim so as to provide appropriate supply to each of the AFS incumbency jobs. The goals here were to (a) populate each of the AFS jobs gradually during a start-up period of the simulation, and (b) following start-up, to maintain AFS incumbency StaffSizes (the number of simulated airmen actually in each job state) at or near the desired StaffLevels shown in Table B1. In calculating the Tech job states' StaffLevels it was necessary to anticipate attrition in both the RTT and the AFS job states. Airmen in the AFS job states were therefore categorized according to the time remaining in their enlistment. Airmen who were targeted to exit the system as a function of completing their first term of enlistment and for whom a replacement had already been selected into BMT or RTT were classified as "complete," and all others were classified as "continuing." The binary variable StayInJob served as this classification variable with 1 representing "continuing" and 0 representing "complete."

The Tech job states' StaffLevels were a function of:

(a) The number of airmen already in the respective Tech job states;
(b) Expected attrition from RTT over its duration;
(c) StaffLevels for the respective AFS job states;
(d) Expected attrition from respective AFS job states in a given month, and;
(e) The number of "continuing" airmen in the AFS job states, as defined above.

In addition to these considerations, it was necessary to gradually "start-up" the simulation so as to avoid sudden changes in StaffSizes, thus necessitating a very complicated means of calculating BMT and RTT StaffLevels. Essentially, it was necessary to develop an efficient manpower planning system which could adjust to a number of different transition models and which could also be adjusted for various performance and attrition characteristics associated with the model.

The following example illustrates the system using the AFS and Tech jobs for AFS272x0. StaffLevel for AFS272x0 was calculated monthly as:

StaffLevel.AFS272x0 = (Month>2)*[[(Month<45)*(Month-2)*(1638/43)]
* [(Month>=45)*1638]]. (B1)

Months 1 and 2 are used to train "start-up" airmen in BMT, thus StaffLevel.AFS272x0 remains 0 (i.e., the value of the boolean variable "Month>2" is false (= 0) for months 1 and 2). After the first two months (i.e., "Month>2" is true (= 1)), StaffLevel grows by 38 airmen per month (i.e., (Month<45) is true (= 1), * (Month-2) * 1638/43, where (Month-2) equals 1 in Month 3, etc.) until it reaches it maximum on month 45 of 1638 (i.e., (Month>=45) is true (= 1) * 1638). This is the "start-up" phase of the simulation. After this, the StaffLevel remains a constant 1638 as specified in Table B1. Formulae for calculating all AFS job states' StaffLevels are shown in Table B2.

Full term enlistees spend 43 months in the AFS272x0 incumbency job state (i.e., 48 months minus 2 months BMT and 3 months RTT). If there were no attrition, admitting 38 airmen each month into the Tech272x0 job state would provide an adequate manpower supply. However, the Tech272x0 StaffLevel had to take into account attrition from both the Tech and AFS job states, along with the current number of trainees already residing in Tech272x0. This was accomplished as follows:

StaffLevel.Tech272x0 =
StayInJob.sum+[MthsNeed.AFS272x0*cmpd(1,4,-Quitprob.mean)] (B2)

Technical training for AFS272x0 lasts for three months. "StayInJob" is recalculated monthly as a boolean variable (TimeInJob<3) which equals 1 if an airman is expected to remain in the Tech job state, and equals 0 otherwise. Thus, the sum of the variable "StayInJob" represents the number of airmen already in the Tech job state who are not expected to attrit or graduate into the AFS272x0 job state in the current time period. This is element (a) in the functional form specified above for the Tech job states' StaffLevels.

Table B2

Calculation of StaffLevels for AFS Job States

AFS	StaffLevel
272x0	(Month>2)*[[(Month<45)*(Month-2)*(1638/43)]+ [(Month>=45)*1638]]
328x0	(Month>2)*[[(Month<44)*(Month-2)*(1086/42)]+ [(Month>=44)*1086]]
423x5	(Month>2)*[[(Month<44)*(Month-2)*(2270/42)]+ [(Month>=44)*2270]]
272x0	(Month>2)*[[(Month<47)*(Month-2)*(1937/45)]+ [(Month>=47)*1937]]

MthsNeed.AFS272x0 represents the expected need for new airmen in the AFS272x0 job state four months in the future (i.e., 3 months duration of Tech272x0 plus one month for recruitment). This need is adjusted by the average probability of attrition for airmen in RTT (i.e., "Quitprob.mean") compounded for the 3 months the airman remains in training plus the month of transition to the incumbency job [cmpd(1,4,-Quitprob.mean) in Equation B2]. This is element (b) in the functional form for Tech StaffLevels. MthsNeed for AFS272x0 was calculated as:

MthsNeed.AFS272x0 =

[StaffLevel+QuitProb.sum-[StayInJob.Sum+
(cmpd(1,4,Quitprob.Mean.Tech272x0)*StaffSize.Tech272x0)]
+[(Month<45)*38]]*cmpd(1,43,-Quitprob.mean). (B3)

This equation calculates the expected future need for airmen in the AFS272x0 job state, that is, the number of airmen needed in 4 months. When discounted for attrition in training (as above), this is the number of airmen needed to start training in a given month. The components of Equation B3 are as follows. For the first 44 months of the simulation (i.e., the boolean variable "Month<45" equals 0), MthsNeed includes a growth term which provides an increasing number of airmen for the incumbency states. The last part of Equation B3 provides for this start-up function:

[(Month<45)*38]]*cmpd(1,43,-Quitprob.mean).

Thus in a fashion similar to that shown earlier in Equation B2, the number of trainees added is equal to the number needed (38) compounded for attrition over the 43 months of incumbency [i.e., cmpd(1,43,-Quitprob.mean)]. This means of calculating the StaffLevel for AFS272x0 was articulated above in Equation B1, and represents element (c) in the functional equation for the Tech job states' StaffLevels. After "start-up" this represents the constant number of individuals needed for the AFS272x0 job state.

The sum of the variable QuitProb represents the expected attrition from the the AFS job state for a given month. This is element (d) in the functional equation for Tech StaffLevels. Quitprobs for a given month are calculated using the OLS prediction formula shown in Appendix C. The full term of enlistment spent in the AFS272x0 job state is 43 months. Quitprob assumes that the probability of termination is constant over these 43 months.

Just as in the Tech job state, StayInJob.Sum represents the number of airmen remaining in the AFS job state. However, StayInJob for the AFS job states was defined in terms of the number of airmen remaining through the month in which their replacement would have to be selected into RTT, or the number of "continuing" airmen as defined above. Further, since StayInJob was recalculated at the end of each simulated month and StaffLevel was calculated at the beginning of the following month, it was necessary to add one month lag to the calculation. StayInJob.Sum defines element (e) in the functional formula for Tech Stafflevels. Thus for AFS272x0, StayInJob was calculated as:

$$\begin{aligned} \text{StayInJob.AFS272x0} &= (48\text{ mos.}) - (3\text{ mos. training}) - (1\text{ mo. lag}) \\ &= (\text{TAFMS}<45) \end{aligned} \tag{B4}$$

For manpower planning purposes, airmen were considered as residing in an AFS job state once they were transitioned into the AFS's Tech job state. Thus, the simulation attempts to maintain a constant sum of individuals in training and "continuing" airmen. MthsNeed is the difference between the StaffLevel and this sum. StaffLevel and MthsNeed formulae for all Tech job states are shown in Table B2.

BMT StaffLevel was determined in a fashion similar to those for the Tech job states. First, the variable BMTMth served the same role as the variable StayInJob for the Tech job states, except that it was calculated two months earlier in the simulation. For AFS272x0 this was calculated as:

$$\begin{aligned} \text{BMTMth.AFS272x0} &= (48\text{ mos.}) - (3\text{ mos. training}) - (2\text{ mos. BMT}) - (1\text{ mo. lag}) \\ &= (\text{TAFMS}=43) \end{aligned} \tag{B5}$$

Second, BMTNeed served the same role as the variable MthsNeed for the Tech job states. Rather than specifically accumulating the anticipated attrition of individuals in training and incumbency, BMTNeed discounted the observed need for individuals (BMTMth.Sum) by the probablity of attrition in BMT (Quitprob.Mean.BMT) and RTT (QuitProb.Mean.Tech). BMTNeed for AFS272x0 was estimated as:

$$\text{BMTNeed.AFS272x0} = [\text{cmpd}(1,2,\text{-QuitProb.Mean.BMT}) * \text{cmpd}(1,3,\text{-QuitProb.Mean.Tech272x0})] * [[(\text{Month}<45)*38]+[(\text{Month}>=45)*\text{BMTMth.Sum}] + \text{QuitProb.Sum}] \quad \text{(B6)}$$

Finally, the need for Airmen in the four AFS classes was summed in the calculation of BMT StaffLevel (i.e., a global summation, or "BMTNeed.ESum"), added to the number of airmen entering their second month of BMT (StayInJob.Sum.BMT), and adjusted upward by 10% to allow for chance differences in attrition rates from year to year, or:

$$\text{StaffLevel.BMT} = [\text{StayInJob.Sum}+\text{BMTNeed.ESum}+[(\text{Month}<2)*250]]*1.1 \quad \text{(B7)}$$

Overselected Airmen (i.e., those not admitted to Tech training) were transitioned into the OtherAFS job state.

In summary, staffing levels for BMT and Tech job states were determined using a complicated dynamic manpower planning system. The system was designed to be sensitive to time spent in training, attrition, and random variation in staffing. It was capable of maintaining appropriate staffing levels for the AFS job states while adapting to a variety of performance and attrition characteristics associated with various selection and classification models.

Table B3

Calculation of StaffLevels for Tech Job States

AFS	Formulae
272x0	StaffLevel.Tech272x0 = StayInJob.sum+ [MthsNeed.AFS272x0*cmpd(1,4,-Quitprob.mean)] MthsNeed.AFS272x0 = [StaffLevel+QuitProb.sum-[StayInJob.Sum+ (cmpd(1,4,Quitprob.Mean.Tech272x0)*StaffSize.Tech272x0)] +[(Month<45)*38]]*cmpd(1,43,-Quitprob.mean)
328x0	StaffLevel.Tech328x0 = StayInJob.sum+ [MthsNeed.AFS328x0*cmpd(1,5,-Quitprob.mean)] MthsNeed.AFS328x0 = [StaffLevel+QuitProb.sum-[StayInJob.Sum+ (cmpd(1,5,Quitprob.Mean.Tech328x0)*StaffSize.Tech328x0)] +[(Month<44)*54]]*cmpd(1,42,-Quitprob.mean)
423x5	StaffLevel.Tech423x5 = StayInJob.sum+ [MthsNeed.AFS423x5*cmpd(1,5,-Quitprob.mean)] MthsNeed.AFS423x5 = [StaffLevel+QuitProb.sum-[StayInJob.Sum+ (cmpd(1,5,Quitprob.Mean.Tech423x5)*StaffSize.Tech423x5)] +[(Month<44)*26]]*cmpd(1,42,-Quitprob.mean)
732x0	StaffLevel.Tech732x0 = StayInJob.sum+ [MthsNeed.AFS732x0*cmpd(1,2,-Quitprob.mean)] MthsNeed.AFS732x0 = [StaffLevel+QuitProb.sum-[StayInJob.Sum+ StaffSize.Tech423x5] +[(Month<47)*43]]*cmpd(1,45,-Quitprob.mean)

APPENDIX C

DETAILED DESCRIPTION OF MULTIPLE-JOB TERMINATION PROBABILITIES FOR TECH AND AFS JOB STATES

DETAILED DESCRIPTION OF MULTIPLE-JOB TERMINATION PROBABILITIES FOR TECH AND AFS JOB STATES

In the multiple-job simulations, individuals were exited from the system into termination job states on the basis of "QuitProb" values that were determined uniquely for each job state. For the AFS job states, monthly QuitProb values computed as a function of airman aptitude were estimated by regressing historical attrition data (airmen who completed technical training before 30 DEC 84) on AFQT and MAGE percentile scores, and dividing the total predicted attrition rate by each AFS's simulated service length. QuitProbs for the Tech job states were similarly computed as a function of aptitude by regressing historical training attrition data on AFQT and MAGE composite percentiles. The BMT QuitProb was estimated using historical BMT pass/fail data. Regression results for the Tech and AFS job states are shown in Table C1. For example, QuitProb for AFS272x0 was computed as:

$$\text{QuitProb} = [.29466 + .000101*\text{AFQT} + .000485*\text{M} + .000705*\text{A} - .000024*\text{G} + .000646*\text{E}]/43 \tag{C1}$$

Thus every month, each simulated airman had some probability of being exited from the AFS and Tech job states computed from the average attrition probability over the length of the job state and as a function of airman aptitude.

Table C1

Attrition Unstandardized Regression Results

Job State	Mean Attrition Rate	N	R^2	a	AFQT	M	A	G	E
BMT	.026	151	.004	.03500	.00168	-.00044	-.00067	-.00137	.00059
Tech272x0	.129	487	.083*	.57732	.00314	-.00213*	-.00318*	-.00383	-.00102
Tech328x0	.049	266	.037	.25743	.00853*	-.00045	-.00326*	-.00494	-.00285
Tech423x5	.035	965	.017*	.45416	-.00073	.00059	-.00069	-.00011	-.00109
Tech732x0	.014	910	.007	.20222	.00231	.00079	.00010	-.00029	-.00018
AFS272x0	.415	1586	.003	.29466	.00010	.00049	.00071	-.00002	-.00065
AFS328x0	.397	779	.004	.22897	-.00468	.00013	.00134	.00493	.00066
AFS423x5	.402	2364	.002	.45416	-.00073	.00059	-.00069	.00167	-.00179
AFS732x0	.312	2481	.004	.20222	.00231	.00079	.00010	-.00017	-.00132

Note. N = sample size, a = intercept, AFQT and MAGE are in percentile metrics.